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Key Points:
- Significant increases in rainfall intensity are expected at subdaily time scales
- Describes link between subdaily extreme rainfall and atmospheric temperature
- Discusses role of observations and modeling to help understand future change

Correspondence to:
S. Westra,
seth.westra@adelaide.edu.au

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Future changes to the intensity and frequency of short-duration extreme rainfall

S. Westra[1], H. J. Fowler[2], J. P. Evans[3], L. V. Alexander[3], P. Berg[4], F. Johnson[5], E. J. Kendon[6], G. Lenderink[7], and N. M. Roberts[8]

[1]School of Civil, Environmental and Mining Engineering, University of Adelaide, Adelaide, South Australia, Australia, [2]School of Civil Engineering and Geosciences, Newcastle University, Newcastle upon Tyne, UK, [3]Climate Change Research Centre and ARC Centre of Excellence for Climate Systems Science, University of New South Wales, Sydney, New South Wales, Australia, [4]Hydrological Research Unit, Swedish Meteorological and Hydrological Institute, Norrköping, Sweden, [5]School of Civil and Environmental Engineering, University of New South Wales, Sydney, New South Wales, Australia, [6]Met Office Hadley Centre, Exeter, UK, [7]Royal Netherlands Meteorological Institute, De Bilt, Netherlands, [8]Met Office, Reading, UK

Abstract Evidence that extreme rainfall intensity is increasing at the global scale has strengthened considerably in recent years. Research now indicates that the greatest increases are likely to occur in short-duration storms lasting less than a day, potentially leading to an increase in the magnitude and frequency of flash floods. This review examines the evidence for subdaily extreme rainfall intensification due to anthropogenic climate change and describes our current physical understanding of the association between subdaily extreme rainfall intensity and atmospheric temperature. We also examine the nature, quality, and quantity of information needed to allow society to adapt successfully to predicted future changes, and discuss the roles of observational and modeling studies in helping us to better understand the physical processes that can influence subdaily extreme rainfall characteristics. We conclude by describing the types of research required to produce a more thorough understanding of the relationships between local-scale thermodynamic effects, large-scale atmospheric circulation, and subdaily extreme rainfall intensity.

1. Introduction

The potential for the intensity of extreme rainfall to increase with climate change is of significant societal concern, with rainfall-derived floods being one of the most costly and dangerous natural hazards worldwide [*Ahern et al.*, 2005; *Knapp et al.*, 2008; *Hallegatte et al.*, 2013]. In 2011 alone, the cost of global flood damages was estimated to be $70 billion, with more than 6000 fatalities [*Centre for Research on the Epidemiology of Disasters*, 2014]. Therefore, it is critical to understand the changing behavior and impacts of extreme rainfall to support rural and urban planning policies and the design of flood protection infrastructure.

The first formal detection of human influence on observed daily extreme rainfall intensification was provided by *Min et al.* [2011] (although see also *Kiktev et al.* [2003] and *Kiktev et al.* [2007]), and evidence that links specific extreme weather events or an increase in their number to anthropogenic climate change is continuing to build [e.g., *Coumou and Rahmstorf*, 2012]. Extreme daily rainfall intensity and/or frequency has increased over most continents [*Alexander et al.*, 2006], and approximately 65% of areas from which reliable data are available exhibit positive trends for annual maximum precipitation extremes over 1951–1999 [*Min et al.*, 2011]. The globally averaged 20th and early 21st century rate of increase in annual maximum daily rainfall intensity was recently estimated to be between 5.9 and 7.7% per °C of globally averaged near-surface atmospheric temperature [*Westra et al.*, 2013a]. This average consists of greater rates of change in the topics and the high latitudes of the Northern Hemisphere [see also *Groisman et al.*, 2005], and lower rates recorded in the drier midlatitudes. Daily or longer time scale outputs from general circulation models (GCMs) also suggest that extreme rainfall intensities will increase with global warming [*Meehl et al.*, 2007] with a sensitivity of about 6% per °C globally but with large model variability [*Kharin et al.*, 2007].

In parallel with the advances in understanding changes to daily-scale rainfall, it is becoming increasingly clear that analysis and framing of questions in terms of subdaily rainfall extremes is becoming more critical [*Trenberth*, 2011]. Evidence is building that atmospheric temperatures can lead to more extreme rainfall over short time scales (up to a few hours), potentially also influencing the temporal distribution of the rain [*Lenderink and van*

Meijgaard, 2008; *Haerter and Berg*, 2009; *Lenderink and van Meijgaard*, 2009; *Haerter et al.*, 2010; *Berg et al.*, 2013; *Westra et al.*, 2013b]. A common conclusion to these studies is that subdaily extreme rainfall is intensifying more rapidly than rainfall measured at daily time scales. This could have significant societal consequences, since floods produced by short-duration rainfall (often referred to as "flash" floods [*Georgakakos*, 1986]) are often more hazardous than slower-onset floods because of the difficulty in providing sufficient warning and mobilizing emergency response [*Ahern et al.*, 2005].

Despite the importance of understanding subdaily rainfall from both a scientific and impact-centered perspective, we currently do not have a complete picture of how subdaily extreme rainfall patterns might change in a future climate [*Boucher et al.*, 2013; *Collins et al.*, 2013]. Quality-controlled global rainfall data at subdaily time scales are still unavailable, and modeling studies capable of resolving the physical processes that cause subdaily extremes are scarce [e.g., *Wakazuki et al.*, 2008; *Knote et al.*, 2010; *Pan et al.*, 2011; *Argüeso et al.*, 2013; *Kendon et al.*, 2014]. There are also several alternative hypotheses about the mechanisms that can cause subdaily extremes to increase with atmospheric temperature [*Lenderink and van Meijgaard*, 2008; *Haerter and Berg*, 2009; *Lenderink and van Meijgaard*, 2009], with potential implications for their use in future predictions. The potential for highly localized effects, such as those due to orography, have also been identified recently [*Siler and Roe*, 2014], and these local conditions and rainfall responses can potentially confound attempts to draw more general conclusions at global or continental scales.

In this review, we critically examine whether extreme subdaily rainfall has intensified—and will continue to intensify—as a result of climate change. Given the scientific appreciation of the link between greenhouse gas emissions and changes to atmospheric temperature, we commence by reviewing theoretical and empirical perspectives on the association between subdaily rainfall intensity and atmospheric temperature (section 2). This is followed by a review of observational studies (section 3) that describe how extremes have changed over the instrumental record, and modeling-based studies (section 4) that investigate how extreme rainfall might change in a warmer climate. The relationship between extreme rainfall and flood impacts is then explored (section 5), focusing on the diversity of definitions of "extreme" rainfall used in the climate science and flood hydrology literature and investigating the role of event time scale and the wider meteorological context in influencing flood risk. Finally, knowledge gaps are identified, and potential directions to improve our predictions of subdaily extreme rainfall are described (section 6).

2. The Relationship Between Subdaily Rainfall and Atmospheric Temperature

2.1. Theoretical Basis of Clausius-Clapeyron Scaling of Extreme Rainfall

Atmospheric temperature strongly influences the intensity of extreme rainfall, as warmer air is capable of holding more water than cooler air, and therefore has the potential to provide more moisture to rainfall events. In view of global warming—and the expected intensification in rainfall extremes [*Trenberth et al.*, 2003]—it is important to understand the relationship between rainfall intensity and atmospheric temperature.

There are simple physical reasons that the intensity of extreme rainfall might be expected to increase in a warmer climate. The capacity of the atmosphere to hold water is governed by the Clausius-Clapeyron (CC) equation—an expression of the fundamental relationship between the water-holding capacity of a gas and its temperature. The equation expresses the saturation pressure of water vapor e_s as a function of absolute atmospheric temperature (T) (in Kelvin), according to

$$\frac{\partial e_s}{\partial T} = \frac{l_v e_s}{R_v T^2},$$

where l_v is the latent heat of vaporization (2.5×10^6 J kg^{-1} at 0°C—this is a very weak function of temperature) and R_v is the gas constant (461.5 J kg^{-1} K^{-1}). Linearizing this equation around 0°C and filling in the above values gives

$$\frac{\partial \ln e_s}{\partial T^*} \cong 0.073(1 - 0.007T^*),$$

where T^* is the temperature in degrees Celsius. The actual saturation specific humidity q_{sat}, which is the mass of water vapor per kg of air, is then given by

$$q_{\text{sat}} = \frac{\varepsilon e_s}{p - (1-\varepsilon)e_s} \cong \varepsilon \frac{e_s}{p},$$

where ε is the ratio of the gas constant for dry air to that of water vapor (0.622) and p is the atmospheric pressure (Pa). Since we are considering the surface with a pressure of 10^5 Pa, the vapor pressure is only in the order of 1% of the actual pressure. Thus, the saturation-specific humidity is by good approximation exponential and increases by ~7% per degree at 0°C and ~6% per degree at 24°C. Assuming constant relative humidity, this would lead to an increase of moisture available to rainstorms at the Clausius-Clapeyron rate. In the absence of large changes to circulation patterns [*Trenberth et al.*, 2003; *Pall et al.*, 2007], and possible decreases in relative humidity predicted for some land areas [*Collins et al.*, 2013], we might therefore expect to see increases in the intensity of rainfall due to the enhanced transport of moisture into regions of net moisture convergence.

This theoretical argument suggests a relatively uniform sensitivity of extreme rainfall to atmospheric temperature. *Westra et al.* [2013a] have confirmed from long-term records that the median intensity of observed annual maximum daily rainfall is increasing a rate of 5.9% to 7.7% per °C globally averaged near-surface atmospheric temperature, but with significant variation by latitude. The greatest temperature sensitivity is found in the tropics and at higher latitudes. In another global study, *Utsumi et al.* [2011] found that extreme daily rainfall intensity increases monotonically with daily local surface air temperature at high latitudes but decreases monotonically in the tropics. At midlatitudes, intensities increase at low temperatures and decrease at high temperatures, and this has been attributed to decreases in wet event duration [*Utsumi et al.*, 2011].

2.2. Empirical Investigation Into the Clausius-Clapeyron Scaling Hypothesis

2.2.1. The Observed Relationship Between Hourly Rainfall and Temperature

There is emerging evidence of a super-CC relationship for hourly extremes [e.g., *Utsumi et al.*, 2011; *Mishra et al.*, 2012b], with increases in extremes observed at rates about double the CC scaling rate for temperatures higher than 12°C [*Lenderink and van Meijgaard,* 2008, 2010; *Berg et al.*, 2013]. Using data from the Netherlands, *Lenderink and van Meijgaard* [2008] presented the first analysis of how extreme percentiles of hourly rainfall intensity vary with surface temperature. Their analysis, based on earlier work by *Klein Tank et al.* [1995], involved binning hourly rainfall data according to daily mean temperature and calculating the statistics from the rainfall data in each bin. Considering wet hours, they found that the 99th and higher percentiles increased with temperature at approximately the CC rate of 7% per °C for temperatures up to 12°C and at double this rate for temperatures up to 22°C.

The methodology of *Lenderink and van Meijgaard* [2008] has subsequently been used to analyze the scaling relationship between atmospheric temperature and extreme rainfall intensity in a number of regions worldwide. Several studies have found a CC or super-CC dependence for hourly extremes at temperatures in excess of ~12°C to ~15°C, but regional differences with lower than CC scaling have also been observed [*Shaw et al.*, 2011; *Mishra et al.*, 2012b]. Regions considered thus far include Europe (the Netherlands, Belgium, Switzerland, and Germany [*Lenderink and van Meijgaard,* 2008, 2010; *Lenderink et al.*, 2011; *Berg and Haerter*, 2013; *Berg et al.*, 2013; *Loriaux et al.*, 2013]), Australia [*Hardwick-Jones et al.*, 2010], North America [*Shaw et al.*, 2011; *Mishra et al.*, 2012b], Hong Kong [*Lenderink et al.*, 2011], China [*Yu and Li*, 2012] and Japan [*Utsumi et al.*, 2011]. In addition to these gauge-based analyses, several studies examined the dependence between tropical extreme rainfall intensity and temperature using satellite data [*Allan et al.*, 2010; *Lau and Wu*, 2011] and also find evidence of super-CC scaling. Interestingly, in regions where daily mean temperatures above 24°C are well sampled, changes in the scaling relationship above ~24°C show decreasing extreme rainfall intensity with increasing temperature [*Hardwick-Jones et al.*, 2010; *Lenderink et al.*, 2011; *Utsumi et al.*, 2011].

Thus, rather than exhibit a consistent scaling rate of approximately 7% per °C as expected from the discussion in section 2.1, observational studies have shown rates of up to double the CC rate for temperatures between ~12°C and ~22°C and negative scaling rates for higher temperatures. The typical behavior of the observed scaling of rainfall intensities with temperature is shown in Figure 1a.

The observed relationship between hourly extreme rainfall intensity and temperature is complex. In many studies, surface temperature has been used as a proxy for evaluating whether atmospheric water vapor also scales according to the CC relationship. The main difficulty of this approach is that many atmospheric variables that influence rainfall intensity covary with temperature, so the effect of temperature (or moisture) on precipitation extremes is difficult to separate from the combined effects of multiple atmospheric variables [see, e.g., *O'Gorman*, 2012]. Thus, interpreting the observed scaling requires an

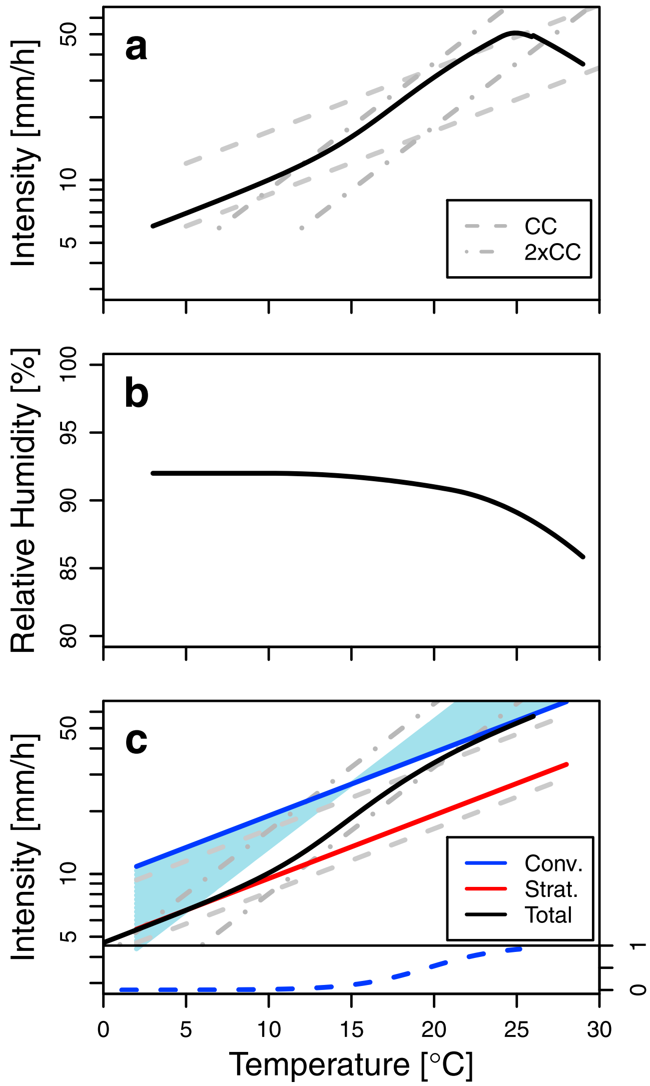

Figure 1. Conceptual diagram of the observed relationship between temperature and extreme rainfall intensity as understood from empirical studies. (a) The basic behavior of higher rainfall intensity percentiles (solid black line) with CC scaling (long-dashed black lines) below about 12°C, super-CC scaling (dot-dashed black lines) between 12°C and 24°C, and negative scaling for temperatures above 24°C. (b) Typical pattern of observed decrease in relative humidity for higher temperatures [*Hardwick-Jones et al.*, 2010; *Berg and Haerter*, 2013]. (c) The hypothesis [*Haerter and Berg*, 2009] of the super-CC scaling being caused by a shift from a stratiform (red) to a convective (blue) weather regime. The inset in Figure 1c shows the relative contribution of convective rainfall to total rainfall.

understanding of the interactions between atmospheric variables and the physical processes that cause them to change. Two processes have been identified as having a particularly large influence on the scaling: changes to atmospheric moisture availability with increasing temperature (discussed in section 2.2.2) and changes to the frequency of atmospheric circulation patterns and the mechanisms that produce rainfall (discussed in section 2.2.3).

2.2.2. Influence of Moisture Availability on the Observed Scaling

Temperature has been used as a proxy for atmospheric water vapor, as direct water vapor observations are scarce. However, the connection between the variables is complex, as shown in investigations of relative humidity as a function of temperature [*Hardwick-Jones et al.*, 2010]. Furthermore, near-surface temperatures can change during the rainfall event itself [*Haerter et al.*, 2010], and this can potentially influence the scaling results. Daily mean temperature therefore has been used to minimize such effects, as it is generally more strongly related to the temperature of the air masses, and was found to produce similar results to maximum daily temperature in a study at 137 locations in Australia [*Hardwick-Jones et al.*, 2010].

Changes in relative humidity were shown by *Hardwick-Jones et al.* [2010] to affect the scaling relationship at high temperatures. They found a reduction in relative humidity above ~24°C, suggesting that moisture availability may decline as temperature increases (Figure 1b). Thus, moisture availability does not increase endlessly with temperature, and may limit the extreme rainfall intensities above a specific temperature threshold. However, because the results were presented in terms of relative humidity, it is unclear whether the total moisture content is decreasing with temperature or whether it is only the moisture content relative to the atmosphere's moisture-holding capacity that is changing [*Berg et al.*, 2009].

Dew point temperature T_d has been used as an alternative measure with which to investigate the combined effect of atmospheric temperature and moisture availability. Dew point represents the actual absolute specific humidity q_v of the atmosphere directly, and is defined by

$$q_{\mathrm{sat}}(T_d) = q_v$$

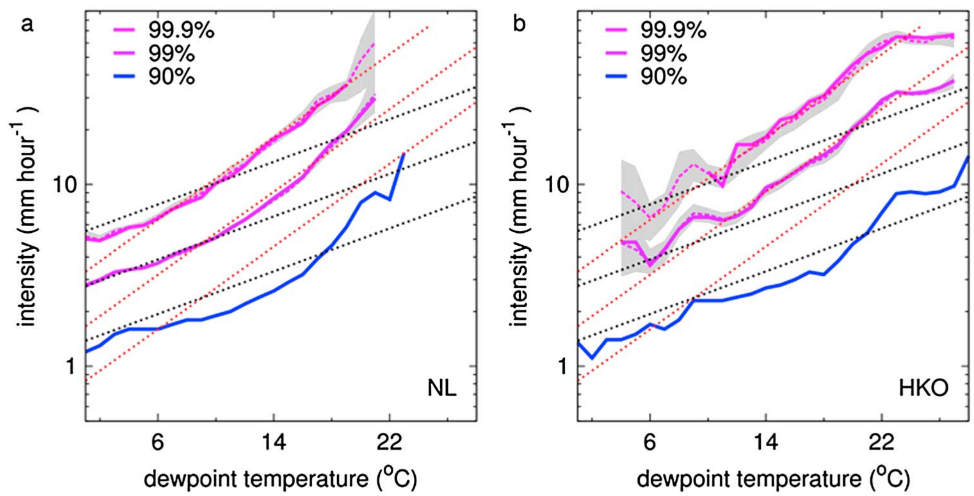

Figure 2. Dependency of hourly rainfall extremes on dew point temperature taken 4 h before the rainfall measurement. (a) The results for 15 years of data from 28 stations in the Netherlands and (b) the results from a 118 year time series from Hong Kong (reproduced from *Lenderink et al.* [2011]).

The difference between temperature and dew point temperature is referred to as the dew point depression and provides a direct measure of relative humidity. Assuming a constant relative humidity, a 1°C temperature rise implies a 1°C rise in dew point temperature. This follows from the fact that q_{sat} is to a very high degree exponential for small temperature perturbations.

When using dew point temperature measurements 4 h before the rainfall event, *Lenderink et al.* [2011] found very similar scaling for hourly rainfall extremes in both Hong Kong and the Netherlands for dew point temperatures up to 22°C. Above 22°C, the dependency on dew point temperature disappeared and no further increases in intensity were observed (Figure 2). Analysis of the same data, but using surface air temperature instead of dew point temperature, clearly identified a peak in rainfall intensity increases at around 24°C and a decline thereafter. These results suggest that the actual moisture in the atmosphere is a better predictor of rainfall intensity than temperature itself. Results using dew point temperature for the inland regions of Canada also found that relative humidity is a limiting factor for the highest temperature range [*Panthou et al.*, 2014].

Besides using surface humidity (or, equivalently, surface dew point temperature), several studies investigated the relation between extreme rainfall and total precipitable water (the column integral of water vapor). The probable maximum precipitation—the largest accumulation of precipitation possible at a location—has been linked to precipitable water [*Kunkel et al.*, 2013b]. In the tropics the onset of convection and precipitation can be described as a phase transition, with strong increases in precipitation near a critical value of the water vapor path [*Peters et al.*, 2009]. Trends in precipitation extremes in the United States also have been linked to precipitable water changes [*Kunkel et al.*, 2013a], although the study also suggests that dynamical factors are likely to be important.

2.2.3. Influence of Rainfall Type on Scaling

Haerter and Berg [2009] argued that super-CC scaling could arise through changes in the dominant rainfall generating mechanisms with temperature, even if each rainfall type scales at the CC rate as depicted in Figure 1c. In particular, they argued that (a) convective extremes are by nature more intense and have shorter durations than large-scale rainfall and (b) the proportion of extreme rainfall which is convective increases with atmospheric temperature. This hypothesis was confirmed by *Berg et al.* [2013], who separated convective from large-scale stratiform rainfall in observational records for Germany and showed that changes in rainfall types with temperature can influence the scaling relationship. However, there also remains a clear super-CC rate of change for convective rainfall alone, indicating that super-CC scaling cannot be explained solely by changes in the rainfall type.

Convective and large-scale rainfall have different spatial and temporal scales, so that one would expect changes in rainfall intensity with temperature to depend on the temporal and spatial scale of the analysis. For example, super-CC scaling is not present in daily rainfall irrespective of whether a super-CC scaling is

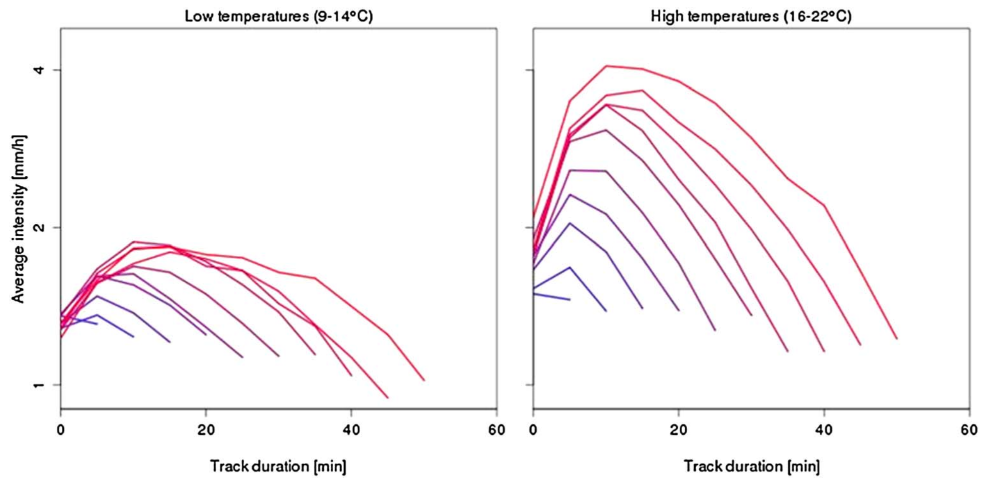

Figure 3. Intensity profiles of tracks of convective rainfall of different durations and for surface temperatures in the range (a) 9–14°C and (b) 16–22°C. Colors from dark blue to bright red indicate tracks of durations from 5 to 60 min, respectively. Reproduced from Figures 8c and 8d from *Moseley et al.* [2013].

found for hourly extremes or not [*Lenderink and van Meijgaard*, 2008]. On the other hand, at a 10 min sampling interval a scaling of close to 2 × CC was obtained for rainfall intensity as dew point temperature increased from 3°C up to 22°C [*Loriaux et al.*, 2013].

Hardwick-Jones et al. [2010] found that the event time scale has a strong influence on the relationship between extreme rainfall intensity and temperature, especially for tropical Australia, with the strongest scaling at resolutions of 30 min or shorter, and weaker scaling for longer durations. Interestingly, *Utsumi et al.* [2011] also found temporal resolution dependence in their results for Japan, but with 10 min data exhibiting a lower rate of temperature change than the hourly and coarser-resolution data. The reason for the differing conclusions between these studies is currently not known.

Time scale dependencies of rainfall extremes were investigated in more detail by *Haerter et al.* [2010] using a 5 min resolution data set for Germany. A break point was identified at around 30–60 min resolution for selected rainfall intensity percentiles, where the extreme percentiles increased at an exponential rate for finer resolutions and as a power law for coarser resolutions. The break point indicates that event durations are typically less than 1 h, and this was confirmed when the durations of individual events were calculated. The researchers also found that temperature dependence was reduced when the total amount of rainfall during an event, rather than its intensity, was considered: as temperature increases, event duration decreases, leading to decreases in the accumulated rainfall yield.

Temporal and spatial scales were also investigated by *Berg et al.* [2013] using a large set of 5 min resolution gauge data, as well as 5 min 1 × 1 km^2 horizontal resolution radar composite images over Germany. They found that event durations (as recorded by the gauges) and event areas (as revealed by frozen time radar fields) had comparable statistics, for example, in terms of the shape of the intensity distribution and mean event intensity. The event duration was scaled with the square root of the area, so that the duration was proportional to the diameter of the rainfall event. The separation of convective rainfall and large-scale stratiform rainfall revealed weak scaling of extreme rainfall with temperature for stratiform events, but super-CC scaling for convective events. Again, the scaling rate decreased as temperatures increased, leveling off at surface air temperatures >20°C.

Moseley et al. [2013] extended this analysis by calculating event tracks from the radar data and found near CC scaling for extreme stratiform tracks, and >2 × CC scaling for convective events. They also found a clear event life cycle for convective events, with a peak in intensity occurring at the end of the first third of the event (Figure 3). The increase of event peak intensity with temperature was found to be greater for longer duration events. Interestingly, because the maximum (instantaneous) intensity during the rainfall event also increases with event duration, these results are consistent with the finding by *Hardwick-Jones et al.* [2010] that the highest temperature scaling rates occurred for the shortest fixed-time intervals.

The role of atmospheric temperature in influencing the within-day distribution of rainfall was reinforced by *Westra et al.* [2013b]. This study showed that although the within-day rainfall distribution varied significantly by latitude and by season across Australia, a significant fraction of the variation could be explained by atmospheric temperature. Cooler latitudes and seasons tended to have rainfall distributed more evenly throughout the day compared with warmer latitudes and seasons. Under the hypothetical condition where total daily rainfall does not change, the maximum within-day 6 min rainfall intensity increased by between 4.1% and 13.4% per °C, whereas the fraction of each wet day that did not experience rainfall increased by between 1.5% and 3.5% per °C. Similar conclusions were made by *Gyasi-Agyei* [2013] who also examined Australian rainfall and *Beuchat et al.* [2011] who focused on rainfall in Switzerland. Consistent with *Hardwick-Jones et al.* [2010], *Beuchat et al.* [2011] observed that the scaling relationship between rainfall and atmospheric temperature is likely to depend on the time scale of the rainfall event.

2.2.4. Summary

Based on the observational results described in the previous sections, the complex scaling relationship between extreme rainfall intensity and atmospheric temperature can be explained as follows:

1. There is widespread evidence for enhanced temperature scaling of short-duration (hourly or subhourly) and small spatial-scale rainfall extremes at rates above the Clausius-Clapeyron rate of 6–7% per °C.
2. This enhancement is partly attributable to an increase in the likelihood of convective versus stratiform rainfall occurrence as temperatures increase and partly attributable to the properties of convective rainfall itself.
3. The event time scale also has an important influence on the scaling relationship, with most studies showing greater scaling rates for hourly or subhourly durations compared to daily durations.
4. There is evidence of a limit to the rate of increase—or even a decrease—in extreme rainfall intensity beyond a certain temperature threshold of approximately 24°C. This appears to be associated with decreases in moisture availability at high temperatures, although the mechanism that causes these moisture deficits remains to be investigated. Thus, surface temperature alone is not a good proxy for atmospheric moisture in such cases.

To better understand the physical processes leading to the observed changes, we now look at model-based studies that examine how cloud feedbacks influence scaling.

2.3. Cloud Feedbacks and Scaling

It has long been suggested that the dynamic nature of the temperature-moisture interaction can lead to a super-CC dependency [*Trenberth et al.*, 2003], and in 2009 Lenderink and van Meijgaard posited that feedback from cloud dynamics due to latent heat release could explain the super-CC scaling they had found in subdaily rainfall observations in the Netherlands. The concept of cloud feedbacks provides a mechanism by which surface air temperature and moisture drives cloud formation and behavior in conditions of constant relative humidity, when moisture-laden air tends to converge and become convective cloud. The convergence of water vapor into ascent results in the condensation into cloud droplets and eventually rain. This process produces latent heat, which imparts buoyancy to the cloud compared to its environment. This, in turn, enhances the updraft motions in the cloud, causing convergence of more air and moisture from the surrounding environment into the cloud, and results in a scaling rate that is greater than the rate at which moisture increases with atmospheric temperature.

In a simple entraining plume model of the core of a convective cloud, *Loriaux et al.* [2013] recently found evidence for cloud feedbacks through latent heat release. In their plume model, moisture enters the cloud core both through the cloud base and laterally when the core accelerates through buoyancy effects. In the experiment, uniform temperature perturbations with height are applied, assuming constant relative humidity. Under these conditions, the lateral moisture flux indeed scales according to 2 × CC, while the cloud base moisture flux satisfies CC scaling, giving rise to a total scaling of 1.6 × CC. In this updraft model, however, there is no dynamic feedback from the cloud to the subcloud layer; this is an unrealistic situation since it is well known that downdrafts originating from the cloud strongly influence the atmospheric boundary layer and subsequent cloud development.

Resolving this issue requires modeling of the full three-dimensional (3-D) dynamics of clouds. With the same experimental setup as *Loriaux et al.* [2013], but using a full 3-D mesoscale model of the atmosphere, *Singleton and Toumi* [2013] found in a simulation of a squall line that the velocity at the cloud base had approximate CC scaling, whereas moisture fluxes scaled at a super-CC rate. Repeating the experiment using a different 3-D

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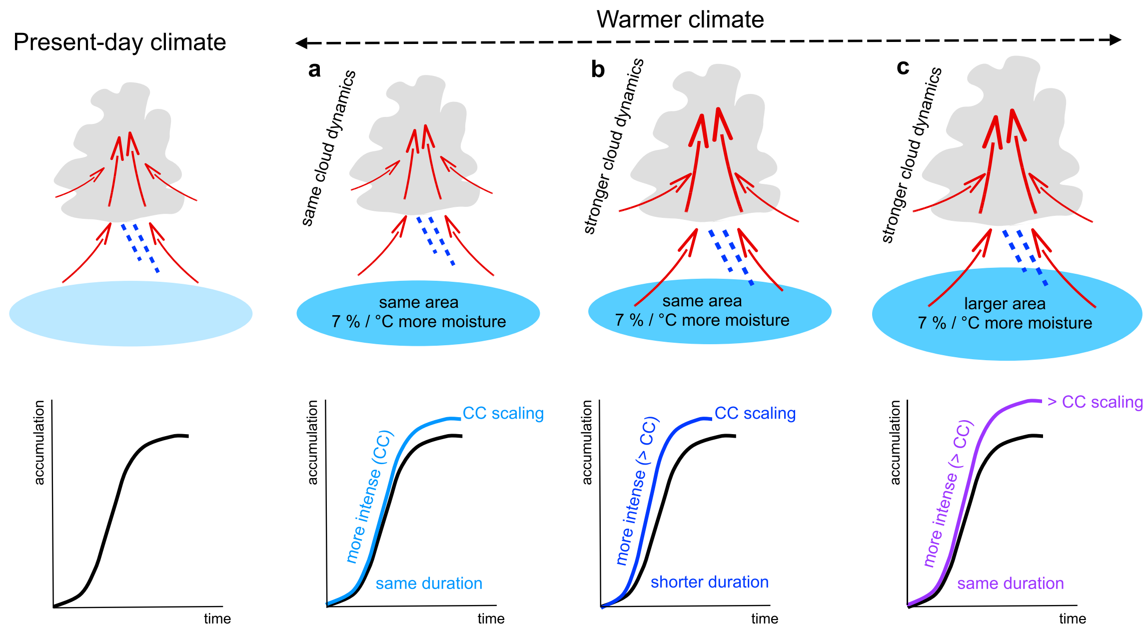

Figure 4. Conceptual overview of cloud feedbacks in relation to moisture availability, depicting (left) the reference situation and three possible future situations: (a) with the same cloud dynamics and warmer and moister air entering the cloud from the same source area, (b) with stronger cloud dynamics, and warmer and moister air entering the cloud from the same source area, and (c) with warmer and moister air entering the cloud from a greater source area due to enhanced cloud dynamics.

mesoscale model, and for a selection of 10 different convective event case studies, *Attema et al.* [2014] found changes in hourly precipitation extremes of 10–13% per degree on average. However, considerable differences between the case studies were found with much smaller dependencies in a small number of cases, thus suggesting a possible physical limitation on increases to the intensity of extreme rainfall events.

Up until this point, we have given a simplified description of how convective rainfall could respond to warming. In reality, mesoscale convective processes are very complex with different structures of organization [*Houze*, 2004]. The work by *Attema et al.* [2014] suggests that the response could depend on the meteorological environment, and therefore on the type of convection as the different cases appear to respond differently. Also, storm movement of fast-moving linear systems could be affected with storms moving faster in a warmer climate [*Singleton and Toumi*, 2013].

Cloud-resolving simulations of tropical convective clouds generally do not show enhanced scaling of rainfall extremes with temperature [*Muller et al.*, 2011; *Romps*, 2011; *Muller*, 2013]. However, the experimental setup of these tropical studies is different from those used for the temperate regions discussed above. In the tropical convective cloud experiments, the model is allowed to run freely to an equilibrium state determined by radiative-convective equilibrium. This results in perturbations closer to a moist adiabat (derived from the difference between two moist adiabats), with enhanced warming at levels higher than at the surface. For a moist adiabatic perturbation, cloud feedbacks do not operate, and higher temperatures do not lead to stronger updraft velocities [*Loriaux et al.*, 2013].

Synthesizing these results, a conceptual overview of cloud feedbacks in relation to moisture availability is developed (Figure 4), which could serve as a basis for further research on how convective rainfall could behave in the context of global warming. We note that we do not attempt to represent all the complexities of mesoscale convection, but we merely focus on simple budget arguments that are expected to be valid in case of warming. In the reference situation (Figure 4, left), moist air enters the cloud through the cloud base and laterally. The cloud accesses moisture from a limited area, depicted schematically in blue. Three possible situations under warmer future conditions are given, all assuming constant relative humidity. In the first situation (Figure 4a), representing the classical CC scaling hypothesis, more moisture enters the cloud due to the higher concentration of moisture per unit of air, whereas the atmospheric motions remain the same. This will limit the total amount of rain from the cloud in its life cycle to an increase of 7% per degree. The intensity (rainfall amount per unit time) will increase at the same rate as it scales with the net moisture convergence and therefore with the increase in moisture content per unit of air. This implies no change to the life cycle of the clouds.

In the second situation (Figure 4b), cloud motions are invigorated, possibly due to the additional latent heat released during the condensation of water vapor. If the cloud still accesses moisture from the same area, this will result in a shortening of the cloud life cycle. The total amount of rainfall from the storm will therefore scale at the CC rate of 7% per degree, but the intensity of rainfall during the storm will scale at a greater rate.

With invigorated cloud dynamics with warming, one could also imagine an increase in the area from which the cloud draws its water. In the third situation (Figure 4c), the increase in the total amount of rain produced by the cloud is therefore not necessarily constrained by the CC relation, and the life cycle of the cloud does not necessarily shorten. However, a larger uptake area will influence convective activity elsewhere to a greater extent and might have implications for occurrence frequencies in both space and time.

2.4. Clausius-Clapeyron Scaling and Climate Change

The Clausius-Clapeyron equation has had a prominent role in theoretical considerations of how rainfall might change with global warming [*Trenberth*, 1999; *Allen and Ingram*, 2002; *Trenberth et al.*, 2003]. On a globally averaged scale, the atmospheric energy balance sets a limit to mean precipitation change of 1–3% per degree global average near-surface temperature—well below the Clausius-Clapeyron rate [*Allen and Ingram*, 2002; *Held and Soden*, 2006]—although with significant regional variations [e.g., *Chou and Neelin*, 2004; *Chou et al.*, 2009; *Muller and O'Gorman*, 2011]. However, as discussed in the previous sections, extreme rainfall intensity is likely to increase at a rate equal to or above the atmosphere's capacity to hold moisture, leading to increases of 7% or more per degree. It is therefore likely that extreme events will increase at the cost of more moderate events.

Intense storms feed on moisture at a spatial scale several times that of the storm scale and practically only from moisture that is already in the atmosphere at the onset of the event [*Trenberth*, 1999]. It has been suggested that changes in daily rainfall extremes should follow the Clausius-Clapeyron relation, since "if the heaviest precipitation events are likely to occur when effectively all the moisture in a volume of air is precipitated out, we might expect the uppermost quantiles of the precipitation distribution to be constrained to increase also as Clausius-Clapeyron" [*Allen and Ingram*, 2002]. Indeed, maximum precipitable water shows robust increases in model simulations [*Kunkel et al.*, 2013b]. Others have argued that changes in the lapse rate of the atmosphere, vertical velocities and convergence of air could cause deviations from the CC scaling rate [*Trenberth et al.*, 2003; *O'Gorman and Schneider*, 2009a; *Sugiyama et al.*, 2010]. The studies described in the previous section suggest that the rate of change will depend on a diversity of factors, including the duration of the storm and the rainfall type.

A very simplified view of climate change is that each extreme rainfall event in the present climate will occur under similar atmospheric conditions in the future climate, but with higher values of temperature and specific humidity (assuming a constant relative humidity). By "similar atmospheric conditions" we mean, among others, similar atmospheric flow conditions (the high- and low-pressure systems) and vertical instability of the atmosphere. If the rainfall event under consideration is convective, then the observed relationships with temperature suggest that its intensity could increase well beyond the CC rate. Indeed, for the Netherlands there appears to be a clear link between the observed long time variations in dew point temperature and variations in hourly extremes, with an inferred dependency close to 10–12% per degree [*Lenderink et al.*, 2011]. This is roughly in agreement with the observed dependency derived from scaling. For Japan, *Fujibe* [2013] found a dependency of the trend in (sub)hourly rainfall extremes on temperature of approximately 10% per degree. However, the applicability of CC scaling relationships in the context of climate change needs to be assessed more thoroughly. Better understanding of rainfall physics and more comprehensive observations of (sub)hourly rainfall, as well as atmospheric temperature and humidity, are essential.

In some dry areas, scaling appears to be lower than CC [*Pall et al.*, 2007; *Wentz et al.*, 2007; *O'Gorman and Muller*, 2010; *Sherwood et al.*, 2010]. However, extreme rainfall intensities over land may also rise at a higher rate than CC as they are more dependent on moisture availability [*Bengtsson et al.*, 2009; *Liu et al.*, 2009], which will be driven by increased latent heating [*Allen and Ingram*, 2002]. There is therefore an urgent need for more extensive observational and modeling studies to investigate the dominant processes that might cause extreme rainfall to change in a future climate. These studies should focus on how those processes are controlled by large-scale circulation and the source of the extreme event's moisture [*Gimeno et al.*, 2012], the (instantaneous) atmospheric availability of moisture at the time of the extreme rainfall event, local-scale features (e.g., orography), time scale, and baseline temperature.

Table 1. Regional Assessment of Observed Trends in Subdaily Rainfall Events Since About the Middle of the Twentieth Century, Unless Otherwise Indicated[a]

Region	Results Summary	Reference(s)
North America and Central America	General increases (USA and western Canada). Some indication that longer-duration storms are wetter but occurring less frequently in the USA. Lack of literature for Central America.	*Brommer et al.* [2007], *Burn et al.* [2011], *Kunkel et al.* [2013a], and *Muschinski and Katz* [2013]
South America	Absence of literature.	
Europe and the Mediterranean	Increases (even in regions with mean decreases) but very dependent on region, season, and duration.	*Leahy and Kiely* [2011], *Wang et al.* [2011b], and *Arnone et al.* [2013]
Africa and Middle East	Lack of literature. In South Africa increases in summer over last two decades.	*Sen Roy and Rouault* [2013]
Asia (excluding Southeast Asia)	More increases than decreases in short-duration events, although eastern China indicates decreases in intensity in late summer.	*Sen Roy* [2009], *Shiu et al.* [2009], *Yu et al.* [2010], *Zhang and Zhai* [2011], *Deshpande et al.* [2012], and *Yu and Li* [2012]
Southeast Asia and Oceania	Increases particularly in very short-duration events but with regional and seasonal variation and duration dependence in Australia. Lack of literature Southeast Asia.	*Jakob et al.* [2011a], *Westra and Sisson* [2011], and *Chen et al.* [2013]

[a]The studies differ substantially in the nature of the data analyzed and the approach used to analyze them, although the term "short duration" typically refers to periods from minutes to hours, and "long duration" refers to periods from multiple hours to days.

3. Interpreting Observational Change: Evaluating Evidence From the Instrumental Record

The previous section described the results from a number of empirical studies that found a strong association between the intensity of extreme rainfall and atmospheric temperature. Given that there has been approximately 1°C near-surface atmospheric warming during the 20th and early 21st centuries [*Hartmann et al.*, 2013], we now review the empirical evidence that rainfall extremes have intensified at rates suggested by temperature scaling arguments. We also investigate the global availability and quality of subdaily rainfall data and discuss possible approaches for overcoming data limitations to better understand historical changes to extreme rainfall at subdaily time scales.

3.1. Assessment of Observed Trends in Subdaily Rainfall Extremes

The majority of observation-based studies that investigate trends in extreme rainfall intensity are based on data recorded at the daily resolution. These include recent assessments at large regional [e.g., *Groisman et al.*,

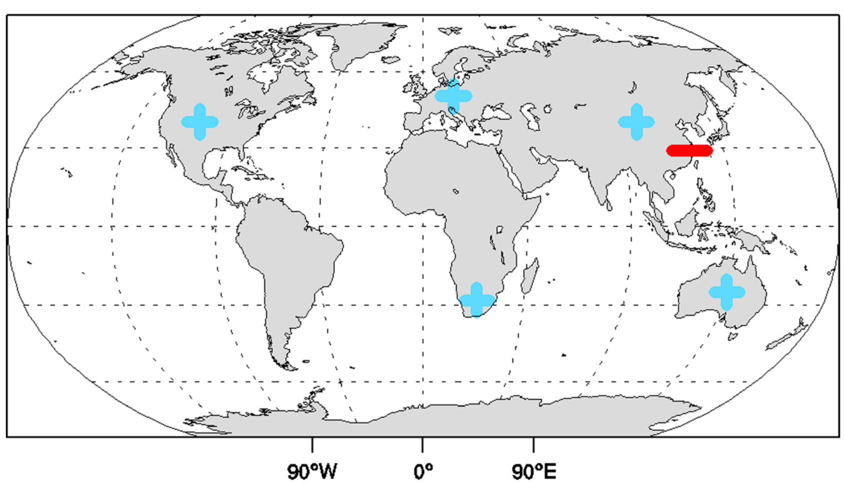

Figure 5. Synthesis of regional trends in subdaily extreme rainfall based on studies shown in Table 1. Increasing trends are shown with plus signs and decreasing trends with minus signs.

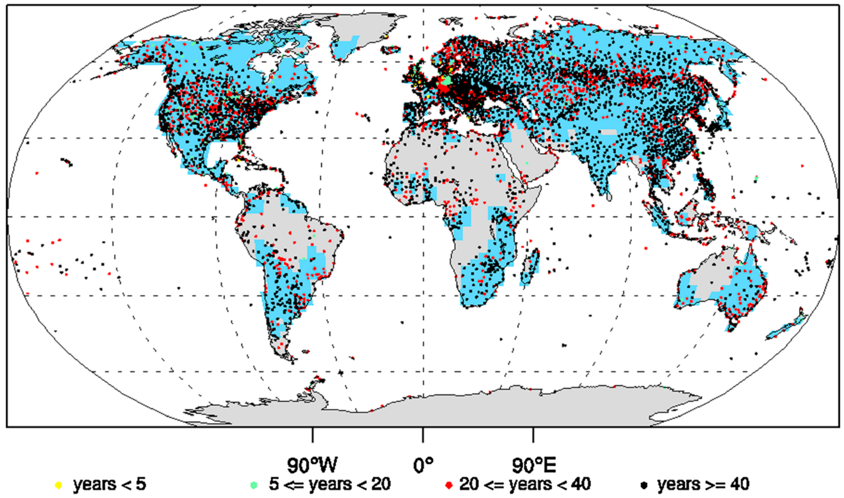

Figure 6. Locations of freely available subdaily precipitation data from the HadISD data set [*Dunn et al.,* 2012, updated from Robert Dunn 13 February 2014]. Dot colors represent station record length. Stations may be open or closed and periods of record are not necessarily coincident nor do they necessarily reflect the amount of nonmissing data in the record. The blue shading represents regions where daily rainfall intensity measures are available from the HadEX2 data set [*Donat et al.,* 2013b] over the period 1951–2010.

2012; *van den Besselaar et al.*, 2012; *Skansi et al.*, 2013] and global scales [*Groisman et al.*, 2005; *Alexander et al.*, 2006; *Donat et al.*, 2013a, 2013b; *Westra et al.*, 2013a]. Most studies point to an increase in rainfall extremes over land since the middle of the twentieth century, but with large regional and seasonal variations [*Hartmann et al.*, 2013]. However, findings presented in section 2 suggest that changes at subdaily time scales may not be reflected in daily rainfall measurements. Therefore, it may not be possible to directly translate conclusions from daily-scale studies to the subdaily time scale.

Most studies on subdaily rainfall extremes have focused on the analysis of individual sites or small regions [e.g., *Jakob et al.*, 2011b; *Lenderink et al.*, 2011; *Fujibe*, 2013]. Far fewer studies have focused on large regional-scale assessments of subdaily rainfall, and an assessment of the current state of knowledge of the long-term temporal trends in extreme rainfall intensity at the subdaily time scale is limited [*Hartmann et al.*, 2013]. Table 1 and Figure 5 summarize continental-scale results. Although there is inconsistency in the trends from regional studies, on the whole they point to an increase in intensity of short-duration events (minutes to hours). It is also clear that there is a lack of literature for many parts of the world and that the strength of subdaily rainfall trends varies regionally, seasonally, and by duration. As will be described below, this can be partly attributed to the quality and availability of the underlying data, and the methodological framework used to assess changes. It is also possible that local climatic factors mean that we can expect some differences between regions.

3.2. Subdaily Rainfall Data Availability

The relative paucity of studies investigating trends in subdaily rainfall extremes is largely attributable to the lack of long, high-quality observational records at subdaily time scales. In Australia, for example, there are more than 17,000 daily-read gauges of which more than 1,700 have records that are more than 40 years long, whereas there are only approximately 2300 subdaily stations with a median length of 9 years [*Westra et al.*, 2012]. Subdaily rainfall records are also typically interspersed with significant periods where the measurement equipment malfunctions, and access to the data by the international research community has often been restricted because few countries have the capacity or mandate to freely distribute high temporal resolution data [*Page et al.*, 2004].

International efforts to collate subdaily rainfall data have been made, and data sets have been developed (e.g., the Hadley Centre Integrated Surface Database (HadISD) data set) [*Dunn et al.*, 2012], but the length of available records is limited. Figure 6 shows that the longest records are distributed across the regions with good data coverage, with the majority of these freely available stations having at least 20 years of data. More data are available at the local and national scales in some countries but access is often limited to researchers with contacts within each country. Data quality remains a serious issue, with varying amounts of quality control performed.

3.3. Measuring Subdaily Rainfall

There are significant differences in subdaily rainfall measurement techniques over time and across different countries, with potential implications for studies that evaluate changes in subdaily rainfall intensity. In operational networks, the tipping bucket rain gauge (TBRG) is one of the most common technologies used to measure subdaily rainfall occurrence and intensity [*Habib et al.*, 2001; *Hill*, 2013]. The TBRG contains two small buckets that balance on a central axis. As rainfall enters the gauge via the funnel and siphon, one of the buckets fills up and tilts downward. When this bucket is full, it empties due to the angle of the bucket and at the same time makes contact with an electrical relay that records the tip. The upper bucket then starts to fill and the process is repeated [*World Meteorological Organization*, 2008b]. The bucket size typically varies from 0.2 to 1 mm, depending on the expected rainfall rate and intended use of the data. A larger bucket is more appropriate for higher rainfall intensities but will not provide as good discrimination of the rainfall event profile for lower intensities [*Fankhauser*, 1998; *Habib et al.*, 2001]. Larger buckets also generally have larger filters above the siphon leading to fewer problems with blockages. TBGRs are used for urban hydrology and flash flood forecasting to provide emergency management authorities with necessary warnings [*Habib et al.*, 2001] and can also be used to calibrate remotely sensed data.

Alternatives to TBRGs include float gauges, distrometers, acoustic gauges, and weighing gauges. The *World Meteorological Organization* [2008a] suggests that weighing gauges are the only gauges suitable for measuring all types of precipitation. *Lanza and Vuerich* [2009] conducted the first field-based study into extreme subdaily rainfall and found that both the weighing gauges with dynamic stability and the synchronized TBRGs performed well for 1 min resolution measurements.

Sites with long subdaily rainfall records are likely to have used different measurement technologies over the lifetime of the site, which can lead to systematic issues when analyzing time series from a single location. *Changnon and Kunkel* [2006] document the case of a tipping bucket gauge that was replaced with a weighing bucket for a site in Illinois in 1948 and attribute increases in high rainfall rates after 1948 to this change. *Karl et al.* [1993] estimated possible changes to recorded rainfall for 10 Northern Hemisphere countries caused by the introduction of wind shields, changes to the gauge height or new instruments. Although these changes were for liquid and solid precipitation measurements, it is likely that similar changes may be found in rainfall intensities. Furthermore, the earliest records tended to use chart recorders where the trace of rainfall intensity was drawn on a roll of paper around a drum within the instrument, and these have often been digitized, with potential for errors due to digitization and damage to the original paper [*Jakob et al.*, 2011b].

Remotely sensed data remain underutilized in studies of subdaily rainfall. Ground-based radar measurements of rainfall events provide information at very high spatial and temporal resolutions [*Borga et al.*, 2000; *Cole and Moore*, 2009]. In many locations, records are now long enough to provide useful time series. Questions remain, however, about the calibration of radar data to match ground-based rainfall measurements, particularly for the highest rainfall rates, where effects such as hail can corrupt the signal [*Chumchean et al.*, 2003]. Attenuation of the radar signal is also a bigger problem for more intense rainfall [*Berne and Krajewski*, 2013]. Intensity-duration-frequency (IDF) and depth-duration-frequency curves have been estimated using radar data [*Overeem et al.*, 2009; *Wright et al.*, 2013] with gauges used for bias correction of the rainfall rates prior to the IDF calculation. *Berne and Krajewski* [2013] suggested that radar can be used to analyze the dynamics and variability of extreme events [*Ntelekos et al.*, 2008], as well as understand the spatial variability of extreme rainfall [*Overeem et al.*, 2010]. Recently, a bias-corrected radar product has been used for this purpose to assess very high resolution regional climate model simulations of short-duration precipitation extremes [*Kendon et al.*, 2014]. This study used a simple scaling approach such that at times when hourly rainfall is a major contributor to the daily total, an upward correction is applied to the hourly radar intensity by comparing daily radar totals with daily gauge totals.

Satellite-based measurements of subdaily rainfall rely on radar and microwave technology, such as for the Tropical Rainfall Measuring Mission (TRMM). The most recent version of the TRMM data is available at relatively coarse time resolutions (e.g., three hourly and daily) and a spatial resolution of only 0.25° [*Liu et al.*, 2012], and questions remain about the capability of TRMM to measure high rainfall intensities [*Iguchi et al.*, 2009; *Rasmussen et al.*, 2013]. Geostationary satellites can also be used for rainfall measurement. The hydroestimator algorithm uses infrared data to provide high spatial (4 km) and temporal (15 min) estimates of rainfall over the United States of America. *Scofield and Kuligowski* [2003] note that satellite data calibration is less robust than ground-based radar calibration and thus is unlikely to be a reliable substitute for ground-based rainfall measurements.

3.4. Data Accuracy and Errors

To understand the significance of trends in observational data sets, it is important to understand the types of likely error and their relative magnitude. The *World Meteorological Organization* [2008b] lists the required accuracy for precipitation measurement. For precipitation intensity, the following targets are suggested: (1) Range: 0.02 mm/h to 2000 mm/h; (2) Resolution: 0.1 mm/h; (3) Uncertainty: 0.1 mm/h for rainfall rates from 0.2 to 2 mm/h, 5% for rainfall rates $>$ 2 mm/h; and (4) Output averaging time: 1 min.

Despite their ubiquitous adoption for operational systems, TBRGs are unlikely to achieve these levels of accuracy [*World Meteorological Organization*, 2008b]. Given that the vast majority of previous and current research into observed trends in subdaily rainfall extremes is based on TBRG measurements, this section focuses on the typical errors in TBRGs that may impact on their ability to achieve the above targets for measurement accuracy. Sources of uncertainty in radar measurements of rainfall rates are reviewed in *Berne and Krajewski* [2013] and are therefore not discussed here in detail.

There has been substantial research over the last 20 to 30 years into identifying and quantifying sources of error in rain gauge measurements. In general, errors in measurement can be divided into two categories [*Molini et al.*, 2005]: errors in catching rainfall and mechanical errors in the TBRG that result in incorrect rainfall intensities being recorded.

Catching errors are generally less important when considering individual high-intensity rainfall events compared to longer-term accumulations [*Adam and Lettenmaier*, 2003; *Molini et al.*, 2005]. Examples of such errors include splashing of drops out of the funnel, wind-induced errors due to poor siting and micrometeorological effects, evaporation of water from the funnel, wetting losses (a problem during the initial part of a storm due to dirt in the funnel), and the higher friction of a dry funnel [*Jorgensen et al.*, 1998; *Habib et al.*, 2001; *Molini et al.*, 2005]. All of these errors can lead to an underestimation of the true rainfall rate; however, the errors are generally small, and *Kunkel et al.* [2013a] note that gauge undercatch is unlikely to be a large problem for heavy rainfall events. *Adam and Lettenmaier* [2003] found that evaporation losses are in the range of 0–4%, while the *World Meteorological Organization* [2008a] lists errors for the other components as 2–10% each for wind effects and losses on the walls of the funnel and 1–2% for splashing.

Mechanical errors associated with the operation of the buckets are of greater concern for extreme subdaily rainfall analyses, with the largest errors occurring at the highest rainfall rates [*Niemczynowicz*, 1986; *Habib et al.*, 2001]. Dynamic calibration of the TBRGs has been suggested to overcome this issue, but is rarely used in practice [*Molini et al.*, 2005]. The size of this error is around 10–15% at rainfall rates of 200 mm/h but depends on the age and condition of the equipment. *Niemczynowicz* [1986] reported similar results with expected errors of up to 10% at a rainfall rate of 300 mm/h and attributed this to the nonlinear behavior of the tested gauges. Mechanical errors associated with the ability to collect rainfall volumes in the siphon that are greater than the capacity of the bucket is also of concern for the highest rainfall intensities. *Maksimovic et al.* [1991] reported that this is likely to occur for rainfall rates higher than 240 mm/h. For these high rainfall intensities, double tips are likely to occur which can cause difficulties in calculating the rainfall intensity from the tip records.

Modeling studies have been undertaken by *Habib et al.* [2001] and *Fankhauser* [1998] to quantify the errors in TBRG measurements. *Habib et al.* [2001] concluded that sampling errors for time aggregations over 1 h were unlikely to be a problem, with the area of largest concern being rainfall measured at time periods shorter than 5 min. *Fankhauser* [1998] looked at the errors introduced by using different bucket sizes and found that, although using smaller buckets is optimal, there is no practical problem with using bucket sizes up to 0.25 mm for urban hydrology. *Ciach* [2003] provided a model of the random errors in TBRG measurements, basing his analysis on a dense network of 15 gauges within an 8×8 m area that assumed that the mean rainfall from the network was the true rainfall. The research found that random errors are highest for 5 min time scales, reducing substantially at time aggregations of 1 h. Random errors are at their highest for low rainfall intensities. It is worth noting, however, that the range of intensities modeled was only up to 30 mm/h, which is much lower than the rainfall rates examined by *Maksimovic et al.* [1991] or Niemczynowicz [*Niemczynowicz*, 1986].

As in all point-based rainfall analyses, the spatial representativeness of the entire network should be considered relative to the study requirements [*Briggs and Cogley*, 1996]. Daily read rainfall gauge networks generally have relatively good coverage in some regions [e.g., *Kunkel et al.*, 2013a] but still may not fully sample areas of high topographic relief [*Briggs and Cogley*, 1996]. Given that there are generally far fewer TBRGs than daily-read gauges, this problem is amplified at the subdaily time scale.

3.5. Alternative Approaches for Quality Assessment and Control

Subdaily rainfall data are mostly maintained by national meteorological agencies, and there is no single agreed approach for quality assessment and control. Furthermore, the required level of measurement accuracy will depend on the purpose of the study; for example, studies that investigate trends in subdaily extremes require long unbroken records, preferably using a single measurement technology, whereas other applications such as operational flood forecasting may not require continuous data or high levels of accuracy. A range of standard procedures for quality assessment and control are presented in Box 1.

Several more sophisticated methods of quality control have recently been proposed. *Bianchi et al.* [2013] considered the use of microwave links to provide quality control of rain gauge data, and the approach appeared to be more successful in detecting rainfall occurrence errors. They suggested that rainfall rates that have multiplicative errors of more than 200% can also be detected reliably. For real-time quality control of rainfall data, *Hill* [2013] proposed a nowcasting system using a dynamic Bayesian network in combination with radar measurements. The combination with radar measurements would ensure that an independent system is used to compare with the gauge-based measurements.

Box 1. Methods Commonly Used for Quality Controlling Subdaily Rainfall Data

1. *Checks on the range of values*. The World Meteorological Organization [*World Meteorological Organization*, 2008a] recommends reasonably broad acceptable limits. *Green et al.* [2012a] found strong spatial differences across Australia of daily data, in terms of the number of flagged values that were true errors. Specific procedures may need to be developed to identify cases when accumulated totals have been substituted for instantaneous measurements.
2. *Changes in values over subsequent measurements*. *Jorgensen et al.* [1998] recommend inspecting the hyetograph shape, with changes in rainfall rates expected to be relatively smooth over time. The approach may be used to identify periods of TBRG malfunction when high tipping frequencies are recorded. *Upton and Rahimi* [2003] developed an algorithm based on the rate of change of intertip times, frequently associated with rapid snow thaw.
3. *Differences between neighboring stations*. Difference between observation stations can be particularly helpful where data have strong spatial correlations [*World Meteorological Organization*, 2008a]. For subdaily rainfall these spatial correlations will be stronger with increasing time period. Spatial checks can also be carried out by aggregating the subdaily rainfall totals to a 24 h total to compare to colocated or nearby daily-read gauges [*Green et al.*, 2001]. Meteorological analysis of the rainfall causative mechanism (e.g., stratiform and convective) can be useful when there are discrepancies between the manual and TBRG measurements [*Jorgensen et al.*, 1998].
4. *Comparison to other types of data for individual events*, including radar images, satellite images, and synoptic maps. This can help validate the recorded temporal and spatial rainfall patterns; however, these checks can be relatively time consuming to implement. Individual large totals, particularly from the predigital era, may also be checked against documentary sources.
5. *Checking a range of time aggregations*. Checks of the range of time aggregations should include the base time resolution and various levels of aggregation. Systematic errors that are not observable at the base time resolution may become obvious when data are aggregated [*World Meteorological Organization*, 2008a]. For example, extended dry periods may be indicative of the TBRG having been out of operation. Using double mass curves or similar, these checks can identify gauges that have become systematically biased, for example, due to blockage or changes in exposure [*Brutsaert*, 2005].
6. *Identification of break points in rainfall time series*. Statistical tests have been applied to aggregated daily data to identify sudden shifts in rainfall series [*Wijngaard et al.*, 2003] caused by, for example, changes in equipment or gauge relocation, but these approaches have not been widely used in conjunction with high-resolution TBRG data. Most meaningful use of such methods, however, requires access to gauge metadata.

3.6. Summary: Assessing Change in the Subdaily Rainfall Record

The lack of long, homogenous, high-quality extreme rainfall data at subdaily time scales represents a significant barrier for further progress in assessing whether subdaily extremes are intensifying under climate change. The absence of comprehensive international repositories for subdaily data, instrumental limitations in the capacity to measure high-intensity short-duration rainfall, inhomogeneities in the instrumentation technology used over time, and inconsistent approaches for quality assessment and control have all acted to hamper progress in this area.

Potential approaches for better using the available subdaily record will be described in section 6; however, it is clear that climate models at different spatial and temporal resolutions will be required to supplement instrumental data in assessing how subdaily extremes can be expected to change under a future climate. The capacity of climate models to simulate subdaily rainfall extremes is the subject of the next section.

4. Learning From Climate Models

Given the substantial difficulties in evaluating changes in subdaily extreme rainfall from instrumental records, the research focus has turned to the application of climate models to produce reliable projections of future subdaily rainfall intensities. Global climate models are designed to represent the average effects of weather on relatively coarse spatial scales (with typical grid sizes of 100 km to 300 km) and have been primarily used to examine changes on monthly or longer time scales. In contrast, subdaily model performance has received relatively little attention to date, with rainfall extremes at these short time scales generally viewed as unreliable due to issues around model resolution and convection parameterization.

Several questions remain with regard to the modeling of subdaily rainfall, including the following: What spatial resolution is required to have confidence in modeled rainfall extremes at different time scales? Can convective parameterizations adequately model rainfall at hourly and subhourly time scales, or are convection permitting—or even convection resolving—spatial resolutions required? These questions that connect space and time scales are increasingly being explored through the use of regional climate and numerical weather prediction models, as well as high-resolution idealized simulations of climate and cloud-resolving models.

4.1. Representing Convection

Large rainfall accumulations on time scales of a few hours are mostly associated with convective storms rather than stratiform systems. *Hand et al.* [2004] looked at severe rainfall events throughout the UK in the twentieth century and found that all events shorter than around 5 h were convective, whereas events up to 12 h had at least a convective component. More than half of the 50 events examined were short-lived convective storms. This gives a strong indication that to generate realistic short-duration rainfall totals, it is crucial to represent convection.

Most climate models are run at spatial resolutions of 10 km or coarser, yet the convective processes associated with extreme rainfall occur on much smaller scales. Convection should not be explicitly represented on a grid that is much larger than the convective elements themselves, which may typically have updraft cores that are only a few hundred meters to a few kilometers across. That is why coarse-resolution climate models must rely on a convection parameterization scheme to compute the estimated average effects of convection over model grid squares. Convection parameterization schemes act to modify the vertical profile of model variables on the grid to take account of the redistribution of the heat, moisture, and momentum associated with the convective cells that cannot be resolved.

Other research suggests the presence of critical phenomena associated with a continuous phase transition between atmospheric water vapor and precipitation [*Peters and Neelin*, 2006]. While the large observational errors involved in the analysis make categorical statements difficult, some aspects of the phenomena do appear to be robust [*Neelin et al.*, 2009; *Peters et al.*, 2009] and provide an additional avenue to test modeled convection. Early attempts to evaluate models using these observed precipitation-water vapor relationships have been attempted by *Sahany et al.* [2012] using a 50 km resolution model and by *Yano et al.* [2012] using a convection-permitting 4 km resolution model. Both studies found that the models were unable to reproduce the critical phenomena identified by *Peters and Neelin* [2006].

Climate and coarse-resolution numerical weather prediction (NWP) models often use mass-flux cloud-plume convection parameterization schemes [e.g., *Tiedtke*, 1989; *Gregory and Rowntree*, 1990; *Kain and Fritsch*, 1990] with updates to the original formulations. They assume that convection is in equilibrium with the larger-scale forcing. The use of a convection parameterization scheme is essential in these coarser-resolution models; otherwise, serious biases will quickly develop because important physical processes are missing. For example, without the convective parameterization, convective instability may build up to the point that the convection is not represented on the grid in a physically realistic manner. This could even, on occasions, lead to model failure. From a rainfall prediction perspective, the problem with convection parameterization schemes is that they are not designed to produce locally realistic rainfall amounts. They respond to the local column convective instability, and because they do not have a direct memory of what happened previously (although they do see a modified environment), they are unable to allow storm advection, development, or decay. This has an adverse effect on the diurnal cycle because organized storm clusters that persist into the evening are not accounted for [*Lean et al.*, 2008]. Current convection parameterization schemes are not able to represent rainfall from storms that continually regenerate in the same location as a result of the storm dynamics or storms that are locally organized because of topographical influence, for example, the Boscastle flood in the UK in 2004 [*Golding et al.*, 2005].

The inability to represent local convective processes is a problem for any model in which convection parameterization is necessary. Even a 10 km grid requires a convection parameterization scheme. Nevertheless, numerous studies have found characteristics of subdaily precipitation improve with increased resolution [*Lee et al.*, 2007; *Sato et al.*, 2009; *Ploshay and Lau*, 2010; *Wehner et al.*, 2010; *Li et al.*, 2011b; *Evans and McCabe*, 2013; *Kopparla et al.*, 2013; *Prein et al.*, 2013; *Tripathi and Dominguez*, 2013]. This is likely to be indicative of a better representation of the mesoscale dynamics [*Lopez et al.*, 2003] and orographic effects that will have the greatest impact at time scales longer than 12 h and for nonconvective systems in winter. In contrast, *Lin et al.* [2012] have found that global model forecasts of convection remain poor, and biases remain even when increasing the resolution.

Another problem arises when the grid size is reduced to less than ~20–40 km, as the model may attempt to represent convection explicitly on the grid when it is not appropriate to do so. If it does, it will generate updrafts that are too large and physically unrealistic. The convection parameterization could be tuned to be more active to stop this from happening, but this only compounds the convection-scheme deficiencies. Furthermore, the assumptions on which an equilibrium convection scheme are based break down at these resolutions because the area of convection is no longer small compared to the area of the grid square [*Swann*, 2001]. This is becoming known as the “grey zone” for convection [*Yu and Lee*, 2010; *Arakawa and Wu*, 2013] and represents a significant challenge for NWP forecast modelers, as well as for the climate modeling community. New approaches in convection parameterization have been developed to alleviate this problem [*Gerard et al.*, 2009; *Yu and Lee*, 2010; *Arakawa and Wu*, 2013], but they do not eliminate it. This is why national meteorological services are choosing to run regional kilometer-scale models to avoid the use of a convection scheme altogether if they have the computational resources available to do so [*Lean et al.*, 2008].

It is often assumed that at grid lengths of less than approximately 4 km (depending on the type of convection) the model is able to represent the convection on the grid sufficiently well without the use of a convection parameterization, even though many of the convective cores are still underresolved. These “convection-permitting” models have proved to be very successful. *Done et al.* [2004], *Kain et al.* [2006], *Lean et al.* [2008], *Hohenegger et al.* [2008], *Roberts and Lean* [2008], *Weisman et al.* [2008], *Schwartz et al.* [2009], *Weusthoff et al.* [2010], and *Kendon et al.* [2012] all point to the benefit of running at this resolution primarily because of the improved realism and potential for more accurate quantitative precipitation forecasts. Convective structures, such as peninsular convergence lines, convective clusters and bands, squall lines, and mesoscale convective systems, are all represented with a high degree of realism. The models are able to successfully discriminate between smaller scattered showers and more organized structures, and between less intense and more intense convection. For example, *Holloway et al.* [2013] showed that in the tropics a 4 km model gave a representation of the Madden-Julian Oscillation which was absent in a model with a grid of 12 km and a convection parameterization scheme.

These results from convection-permitting models are encouraging, but not without problems. Convection is still not properly resolved [*Bryan et al.*, 2003], and this can lead to some artifacts, such as a tendency to produce showers that are too intense [*Hanley et al.*, 2014]. Nevertheless, the models are a big step forward and the best opportunity we currently have to examine possible changes in subhourly rainfall extremes with climate change.

4.2. A Global Perspective: What GCMs Tell Us About Extremes

There are many studies that investigate the simulation of daily, or longer, time scale precipitation extremes in global climate models (GCMs) [*Seneviratne et al*., 2012; *Flato et al*., 2013]. GCM-based investigations into extremes are usually based on relatively "frequent" extreme indices such as those defined by the Expert Team on Climate Change Detection and Indices (ETCCDI), although *Kunkel et al.* [2013b] recently found evidence for future increases in the probable maximum precipitation at the daily time scale from Coupled Model Intercomparison Project phase 5 (CMIP5) GCMs (see section 5.1 for further details on alternative definitions of extremes). Studies using the ETCCDI indicate large-scale statistically significant increases in extreme precipitation during the last century [*Alexander et al.*, 2006; *Donat et al.*, 2013a, 2013b] and into the future [*Sillmann* et al., 2013]. GCMs are typically considered unreliable at subdaily time scales, so that there are few studies that examine changes in subdaily rainfall in GCMs.

Investigations of the diurnal cycle of precipitation show various deficiencies [*Flato et al.*, 2013]. These are due to the limitations of convection parameterization (section 4.1). While many CMIP3 models had a realistic diurnal amplitude, most of the models tended to start moist convection too early over land [*Dai*, 2006; *Wang et al.*, 2011a]. Many CMIP5 models exhibited similar problems with the precipitation peaking several hours too early [*Flato et al.*, 2013]. Problems with the GCM-based diurnal cycle of precipitation have also been found over the oceans, with models producing rain too frequently and the diurnal amplitude underestimated [*Stephens et al.*, 2010].

Improvements in the simulation of the diurnal cycle have been reported in several recent studies, suggesting possible improvements in the representation of other aspects of subdaily rainfall as well. Some have reported improvements with increased spatial resolution of the model generally [*Lee et al.*, 2007; *Sato et al.*, 2009; *Ploshay and Lau*, 2010] or through the use of a superparameterization where a two-dimensional cloud-resolving model is embedded within each GCM grid box [*Khairoutdinov et al.*, 2005; *Pritchard et al.*, 2011]. Superparameterizations are computationally much less expensive than global cloud-resolving models, but there are few examples of them being used to date. Other model improvements targeting particular physical processes, including entrainment in the parameterization of deep convection [*Stirling and Stratton*, 2012; *Stratton and Stirling*, 2012], coupling between shallow and deep convection, and including density currents, have been found to improve the diurnal precipitation cycle over land [*Hourdin et al.*, 2013]. These improvements led *Flato et al.* [2013] to conclude that "the best performing models … appear now to be able to capture the land and ocean diurnal phase and amplitude quite well."

GCMs generally perform poorly in terms of rainfall extremes [*Stephens et al.*, 2010]. Deficiencies include the tendency for heavy rainfall to be too persistent [*Rosa and Collins*, 2013] and errors in the intensity of extreme events [*Kopparla et al.*, 2013]. Simulated rainfall extremes in the tropics have been found to be particularly unreliable [*O'Gorman and Schneider*, 2009b; *Kharin et al.*, 2012]. Again, many of these deficiencies can be traced back to the convection parameterization scheme.

4.3. Downscaling to the Regional Scale

Higher-resolution regional climate models (RCMs, 10–50 km grid spacing) generally improve the representation of daily precipitation extremes relative to GCMs, and there is some evidence that they also offer improvements at the subdaily time scale [e.g., *Maraun et al.*, 2010]. *Lenderink and van Meijgaard* [2008] found that a 25 km RCM can reproduce some of the observed scaling of hourly precipitation extremes with temperature. *Gregersen et al.* [2013] showed that the temporal changes in extreme events are partly reproduced by a 25 km RCM even though the spatial correlation structure is not. *Tripathi and Dominguez* [2013] found that a 10 km resolution RCM is able to capture the spatial structure in three hourly precipitation extremes that are missing in a 50 km version of the same model, while *Evans and Westra* [2012] demonstrated that a 10 km RCM is largely able to capture the diurnal cycle of precipitation. This is consistent with other studies that have found improvements in subdaily precipitation at the 10 km resolution [*Gutowski et al.*, 2003; *Yamada et al.*, 2012; *Prein et al.*, 2013]. However, RCMs also suffer from significant limitations in terms of representing subdaily rainfall, especially at resolutions lower than ~10 km. When using such models, it has proved difficult to reproduce observed extreme rainfall intensities on subdaily time scales [*Hanel and Buishand*, 2010; *Mishra et al.*, 2012a; *Jiang et al.*, 2013]. Nor can the diurnal cycle of convection [*Brockhaus et al.*, 2008] or the spatial characteristics of subdaily extremes [*Gregersen et al.*, 2013; *Tripathi and Dominguez*, 2013] be adequately represented.

Convection-permitting models with grid lengths less than approximately 4 km are commonly used for short-range weather forecasting, and their benefits in terms of representing convection have been discussed in section 4.1. The added value of convection-permitting resolutions has also been seen in longer seasonal simulations. Improvements are found in the diurnal cycle of convective rainfall [*Hohenegger et al.*, 2008; *Lean et al.*, 2008; *Sato et al.*, 2009; *Langhans et al.*, 2013], the spatial structure of rainfall [*Warrach-Sagi et al.*, 2013], and the intensity of the most extreme rainfall [*Prein et al.*, 2013]. These improvements are not simply a consequence of the better resolved orography but are caused by the explicit treatment of convection and the more realistic model dynamics. *Trapp et al.* [2011] used a sequence of daily integrations at 4 km to build up a multiyear climatology of short-duration rainfall over the U.S., which was found to compare well with observations. *Kendon et al.* [2012] carried out a continuous (20 year) length climate simulation with a 1.5 km model over a region of the UK. They showed improved realism in the representation of hourly rainfall, including the duration-intensity characteristics and the spatial extent of heavy rain. Evaluation of the same 1.5 km simulation also revealed an improved realism in the representation of hourly extremes compared to a 12 km resolution model [*Chan et al.*, 2014].

To be confident in a regional climate model's projections of subdaily rainfall extremes, the model must be able to represent the physical processes responsible for any future changes. Convection-permitting models in particular have shown a high degree of realism in the representation of rainfall (including the spatial and temporal characteristics of rainfall across a range of space and time scales, as a function of the meteorological situation). This provides a good indication of their skill in representing the underlying physical processes [*Kendon et al.*, 2012], including their representation of local storm dynamics, providing confidence in their ability to reliably project future any changes in hourly rainfall. Nevertheless, future projections from such regional models are still highly dependent on the ability of the coarser-resolution global driving model to represent variability in the larger-scale flow and future changes in those patterns.

Convection permitting resolution regional models have been used to study the characteristics of particular storm events, including the influence of various parameterizations and other aspects of the model configuration on the simulation of these events [e.g., *Jankov et al.*, 2007; *Liu et al.*, 2011; *Prein et al.*, 2013; *Fiori et al.*, 2014]. Event-based approaches, where selected historical or future weather events in coarser-resolution models are downscaled to storm scale, can also be used to investigate changes in extreme precipitation [*Mahoney et al.*, 2013]. These approaches provide insight into how changes in large-scale parameters may affect small-scale storms potentially at subdaily time scales but do not provide a definitive answer as to whether extreme rainfall will increase or not, as they only examine changes in the intensities of specific events and ignore changes in frequency or changes to the large-scale atmospheric circulation associated with those events.

There are very few studies to date that apply convection-permitting resolutions to long-term climate change simulations [e.g., *Argüeso et al.*, 2013]. Due to their high computational cost, these are generally limited to small domains and often run for a single season. *Knote et al.* [2010] carried out convection-permitting simulations for the summer season over a region of Germany and showed a slight decrease in hourly precipitation extremes. *Wakazuki et al.* [2008] showed an intensification of short-duration precipitation extremes over Japan in the Baiu season in a 5 km model. *Pan et al.* [2011] carried out climate change experiments at 4 km resolution over the western U.S. and showed increases in hourly rainfall in winter and decreases in summer.

A recent study by *Kendon et al.* [2014] carried out continuous multiyear climate change experiments at a 1.5 km resolution over a region of the UK and showed a future intensification of hourly rainfall in summer not seen in a coarser 12 km RCM. This indicates the importance of representing the local storm dynamics (as well as changes in the larger-scale environment) for predicting future change in convective storms. *Kendon et al.* [2014] suggest that previous interpretations of future regional climate change scenarios from coarser-resolution models should be revisited as changes in convective events could have been underestimated. Due to the limited number of climate studies undertaken at convection-permitting scales, it is still not possible to draw broader conclusions from these models on how subdaily rainfall will change under future climate change, although this will likely improve as more high-resolution modeling studies become available.

4.4. Idealized Modeling Experiments

Climate models have also been used in idealized setups, such as aquaplanets, to improve our understanding of the mechanisms underlying precipitation characteristics [*O'Gorman and Schneider*, 2009a; *Li et al.*, 2011a; *Oueslati and Bellon*, 2013; *Hagos et al.*, 2014]. Many of these studies are global in nature and focus on equilibrium characteristics of rainfall.

Cloud-resolving models have been used to investigate the effect of warming on subdaily extreme rainfall in idealized simulations. For the tropics, *Muller et al.* [2011] and *Romps* [2011] found that increases in rainfall extremes with temperature approximately scale with increases in surface water vapor concentrations (i.e., they roughly follow the CC relation). In both studies, the atmosphere is allowed to react to future climate conditions through an equilibrium process. For the midlatitudes, *Attema et al.* [2014] found evidence of super-CC increases of extreme hourly rainfall for an idealized warming perturbation, while *Singleton and Toumi* [2013] found super-CC scaling within a model squall line. Recent work has shown that regional differences in scaling may be explained by differences in atmospheric stability changes [*Loriaux et al.*, 2013]. In particular, if the temperature perturbation is adjusted from a constant to a moist adiabatic increase (considered more representative for the tropics), the scaling decreases to the CC rate. Together, these studies indicate that we may expect considerable increases in subdaily precipitation extremes with warming, at least in some regions, but with uncertainty as to where and to what extent.

4.5. Summary: Predicting Change From Climate Models

Coarse-resolution global and regional climate models are unreliable at subdaily time scales due to deficiencies and inherent limitations in the convective parameterization scheme. Although convective parameterizations are effective at eliminating vertical instabilities in the atmosphere, they do so in a manner that leaves significant uncertainty associated with the simulated subdaily precipitation. While convective parameterizations continue to improve, the current level of uncertainty means that inferences concerning the future change in subdaily precipitation that rely on these parameterizations remain relatively weak.

Model resolutions on the order of a kilometer are required to eliminate the need for a convective parameterization scheme. Such kilometer-scale RCMs are now becoming available, giving a much better representation of convective events. This will increase confidence in their ability to project changes in hourly rainfall extremes.

Evidence from high-resolution climate models, in both real-world and idealized setups, suggests that the intensity of subdaily extreme rainfall is likely to increase in the future. Increases roughly in agreement with the CC relation (~7% per °C) appear most likely in many regions, including the tropics, although evidence suggests that some regions will experience even greater increases in subdaily precipitation extremes, while others may even experience decreases. To better identify regions likely to experience the largest increases in subdaily extremes, further work will be required to bring the results obtained from idealized model simulations together with those from real-world simulations and observations. As high spatial and temporal resolution information becomes available from kilometer-scale RCMs, the data can be used directly as input into hydrological and hydrodynamic models, enabling the assessment of future flood risk.

5. The Relationship Between Extreme Rainfall and Flood Impacts

The potential increase in flood risk due to climate change is often cited as a primary reason for studying changes to extreme rainfall intensity. Whereas the evidence of extreme rainfall intensification is strengthening, there remains significant uncertainty about both the direction and magnitude of changes to flood risk [*Milly et al.*, 2002; *Kundzewicz*, 2005]. This section reviews the different definitions of "extreme" rainfall used in the climate science and flood hydrology literature (section 5.1), the relationship between the duration of extreme rainfall events and catchment characteristics and the magnitude of the ensuing floods (section 5.2), and the broader meteorological context of floods (section 5.3). Each of these aspects will be important when interpreting extreme rainfall projections in the context of projected changes to flood risk.

5.1. When Does an Event Become Extreme?

Research into extreme rainfall events is of interest to a range of disciplines, and this can create difficulties in ensuring consistency in the definitions and types of rainfall statistics that are assessed [*Alexander et al.*, 2009; *Bonnin et al.*, 2011; *Jakob et al.*, 2011a, 2011b]. Furthermore, the detection of trends is dependent on the chosen definition for extreme events [*Suppiah and Hennessy*, 1998], which can create challenges when interpreting these results in other contexts.

In climate science, rainfall extremes generally refer to events greater than some extreme threshold such as the 90th, 95th, or 99th percentile of a cumulative distribution function, usually derived using daily rainfall data. For more extreme events the annual maxima are often analyzed. The annual maxima are also of interest in flood hydrology and are used to estimate more infrequent events required for engineering design. Annual maxima data (together with threshold-excess data) are also commonly used for extreme value analyses, which aim to “quantify the stochastic behavior of a process at unusually large … levels” [*Coles*, 2001]. The theory describes a class of model that allows for extrapolation to events that may be more extreme than those already observed. This is achieved by approximating the behavior of the maxima of a time series through an asymptotic argument [*Coles*, 2001].

Popular definitions of extreme events used in the climate literature include those recommended by the ETCCDI [*Peterson*, 2005; *Zhang et al.*, 2011]. Out of the 27 extreme event indices, 11 refer to precipitation. Two indices use percentiles of daily rainfall (95th and 99th) to calculate the total rainfall resulting from extreme events. Rainfall totals are also used to define extremes, with 10 mm and 20 mm thresholds used to count the number of days of extreme rainfall. The problem with threshold definitions of rainfall extremes is that the thresholds will be exceeded at different rates in different parts of the world, and the relative impacts of these events can vary significantly, for example, due to differences in storm drainage system capacity.

For flood estimation purposes the term extreme generally refers to events much larger than those described above. Flood events commonly analyzed are those with small probabilities of occurring in a given year, such as the 1% annual exceedance probability (AEP) event, which will on average be exceeded only once every 100 years. Although these events are much rarer than those typically used in climate studies (for example, the 99th percentile rainfall event will occur on average 3.65 times per year), these floods are still considered to be relatively frequent in the context of engineering design. For example infrastructure with a 70 year design life designed to the 1% AEP event will have a 50% probability of experiencing a ‘failure’ at least once during its lifetime. Therefore, to minimise the potentially dangerous consequences of floods, there is increasing interest in designing for events much rarer than the 1% AEP event [*Engineers Australia*, 1987; *Perica et al.*, 2013].

The probable maximum precipitation (PMP) is defined as the “theoretical maximum precipitation for a given duration under modern meteorological conditions” [*World Meteorological Organization*, 2009], and its magnitude depends on the time of year, location, and catchment area. The PMP can be estimated using a meteorological analysis of the atmospheric conditions, together with various statistical approaches [*World Meteorological Organization*, 2009]. There is some debate about whether it is appropriate to assign a return period to such an event or if the concept of maximum rainfall is even valid [*Koutsoyiannis*, 1999], although it has been calculated to be between 10^5 years [*Collier et al.*, 2011] and 10^9 years [*National Research Council*, 1994] or provided as a broad notional range, such as 10^4 to 10^7 years [*Nathan and Weinmann*, 1998]. PMP events can be converted to a Probable Maximum Flood, which is often used to design infrastructure that cannot be allowed to fail (for example, because failure can cause loss of life). Examples include the spillways for large dams and the siting of emergency infrastructure such as hospitals and flood evacuation routes. It is also sometimes used to define the limit of floodplains [*NSW Department of Infrastructure Planning and Natural Resources*, 2005].

An illustration of the different definitions of an extreme event used for engineering hydrology is given in Figure 7 [*Nathan and Weinmann*, 1998]. This figure forms part of “Australian Rainfall and Runoff”—a guidance document widely adopted by Australian engineers to estimate flood risk [*Pilgrim*, 1987]. These definitions are clearly much larger than the 99th percentile of daily rainfall or the annual maximum event often used in climate studies, and it is currently not known whether the results of climate studies that focus on such “moderate” extremes can be extrapolated to the events that commonly form the basis for engineering design.

5.2. The Relationship Between Rainfall Duration and Catchment Size

The magnitude of floods caused by extreme rainfall depends on a complex interaction between the time scale, spatial extent, direction, and travel speed of the flood-producing rainfall event; the size, slope, shape,

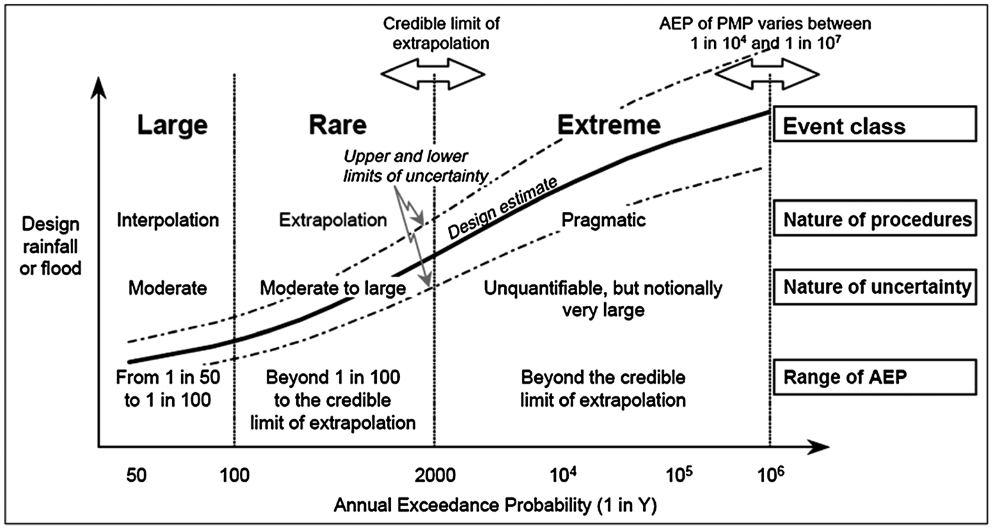

Figure 7. Definitions of large, rare, and extreme flood events used in Australian flood estimation practice [*Nathan and Weinmann*, 1998]. The figure was first published in Book VI of the Australian Rainfall and Runoff (1988 edition) and reprinted here with permission.

and land surface cover (e.g., vegetation, soil type, agricultural, or urban development) of the catchment; the presence of hydraulic structures such as dams and levees that can attenuate the flood hydrograph; and the wetness of the catchment prior to the flood-producing event [e.g., *Milly and Eagleson*, 1988; *Merz and Bloschl*, 2003]. Of these features, the interaction between the catchment size and the spatial and temporal features of rainfall is particularly important: smaller catchments are sensitive to short but intense bursts of rainfall, sometimes lasting only an hour or less, whereas larger catchments are sensitive to extended periods of heavy rainfall lasting for several days or longer.

The relationship between rainfall duration, catchment size, and flood magnitude is encapsulated in a variable known as the time of concentration t_c. This variable is defined as the time at which all of the catchment contributes flow and is often assumed to be equivalent to the time taken for water to travel from the most distant point in the catchment to the catchment outlet [*Chow et al.*, 1988; *Dingman*, 2002; *Brutsaert*, 2005]. Because the extreme rainfall intensity averaged across a duration decreases with increasing duration, the "critical" rainfall duration for a catchment (defined as the duration that, for a given exceedance probability, will cause the greatest flood) is often assumed to be equal to the catchment's time of concentration [*Brutsaert*, 2005].

Numerous empirical relationships have been developed to estimate t_c based on various catchment attributes. Examples include (see *Loukas and Quick* [1996] and *Dingman* [2002] for a discussion of these and other formulations) (1) *Kiprich* [1940] based on small agricultural catchments with areas ranging from 0.003 to 0.5 km^2; (2) *Chow* [1962], based on areas from 0.012 to 18.5 km^2 using data from 20 catchments in the United States; (3) the *National Environmental Research Council* [1975] for the United Kingdom; and (4) *Watt and Chow* [1985], based on data from 44 catchments across the USA. This formulation was developed for catchments with areas from 0.01 to 5840 km^2, and for slopes of the main channel ranging from 0.00121 to 0.0978.

The relationship between t_c and the length of the main stream channel is given in Figure 8 and shows that catchments with main channel lengths of up to ~100 km can be sensitive to the within-day temporal patterns of extreme rainfall events. Catchments of this size are likely to encompass a large proportion of both urban and rural catchments worldwide. As a result, information on extreme rainfall is usually required at durations much shorter than a day; for example, the United States of America's precipitation frequency product and Australia's flood guidelines both provide information on extreme rainfall for durations as low as 5 min [*Engineers Australia*, 1987; *Perica et al.*, 2013], with an updated version of the Australian data likely to provide information at resolutions of 1 min [*Green et al.*, 2012b].

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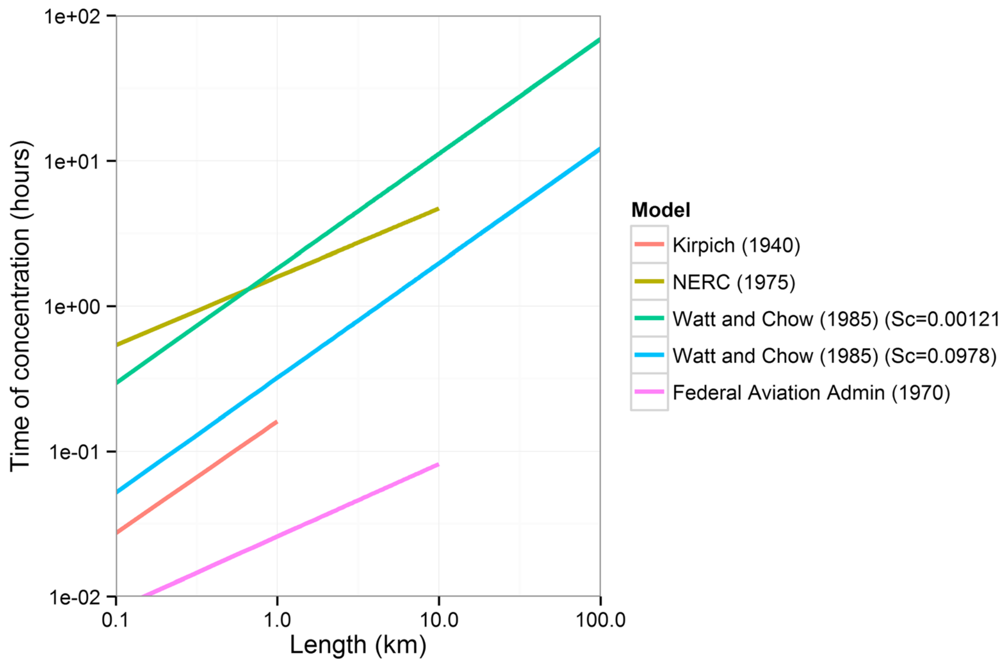

Figure 8. The relationship between time of concentration and catchment length scale, based on a number of widely used formulations described in the main text.

As discussed in section 2, convective and stratiform rainfall occur at different spatial and temporal scales, with short-duration convective rainfall potentially exhibiting a stronger association with atmospheric temperature compared to longer-duration events [*Hand et al.*, 2004]. This suggests that nearby catchments of different sizes can exhibit very different rates of change, depending on the dominant physical mechanisms that operate at each scale.

5.3. Viewing Extreme Events Within Their Context

The focus of this review is on extreme rainfall events with a lifetime of less than a day. However, short-duration flood-producing extreme rainfall events occur within a broader meteorological context, and this context can have a significant influence on the magnitude of the resultant flood. For example, while extreme subdaily rainfall may be the ultimate cause of a flash flood, the severity of the flood may also depend on whether the catchment was dry or wet before the extreme rainfall event [*Cameron et al.*, 1999; *Pathiraja et al.*, 2012]. Similarly, in the coastal zone extreme rainfall events combined with elevated tides and storm surges are likely to produce more severe floods than when any of those three factors occur in isolation [*Svensson and Jones*, 2006; *Zheng et al.*, 2013, 2014].

These situations are collectively referred to as "compound extremes" [*Seneviratne et al.*, 2012; *Leonard et al.*, 2014] and are important since there are meteorological reasons for links between weather features. For example, short-duration extreme rainfall events are often embedded within larger systems, and extreme rainfall can also be associated with extremes of other hydrometeorological variables, such as extreme winds and storm surges, which can exacerbate impacts such as flood damage [*Stommel*, 1963; *Orlanski*, 1975; *Clark*, 1985; *Bloschl and Sivapalan*, 1995; *Zheng et al.*, 2013]. This can be seen in Figure 9.

The interaction between scales poses profound challenges for modeling future subdaily extremes, since changes at small scales cannot be divorced from larger-scale changes, such as alterations in the dominant circulation patterns or modes of interannual variability [e.g., *Pui et al.*, 2011]. To predict future changes in flood risk, therefore, will require a modeling strategy that is capable of resolving rainfall at all relevant scales; this is discussed further in the context of the modeling challenges described in the next section.

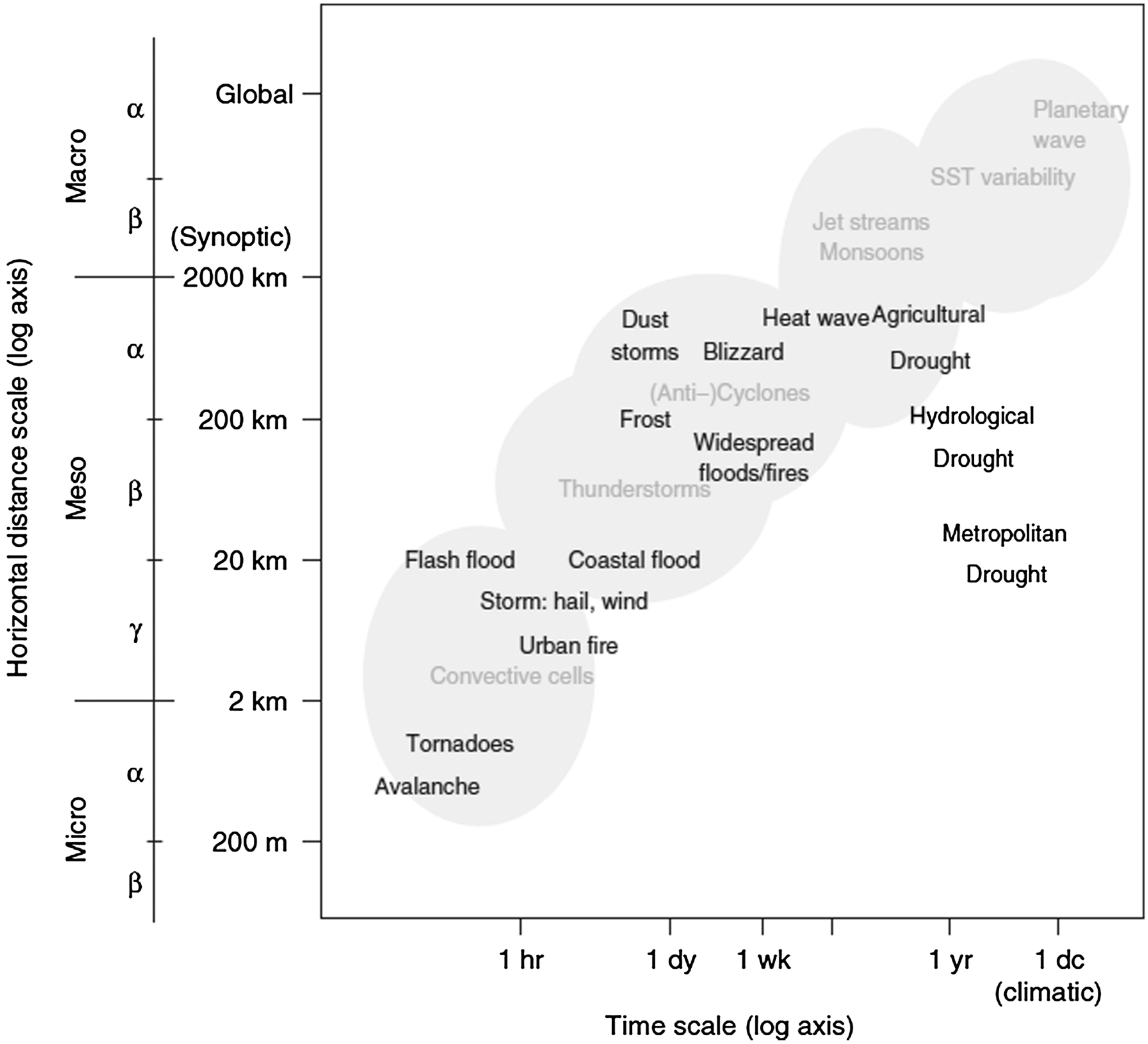

Figure 9. Subdaily rainfall extremes should be viewed within their meteorological context. For example, convective cells may be embedded within cyclonic systems, which occur more or less frequently depending on the state of the ENSO phenomenon. Figure from *Leonard et al.* [2014].

6. Future Directions: Improving Our Capacity to Predict Changes in Subdaily Extremes

At the global scale, extreme rainfall is predicted to intensify as a result of anthropogenic climate change [*Flato et al.*, 2013]. The majority of evidence for this intensification is based on daily time scale observational data and climate modeling output. It is becoming increasingly clear, however, that extreme weather events must be understood at shorter time scales if we are to respond to changes in the risk of natural hazards such as floods that result from changes to extreme rainfall.

This review has discussed the relationship between extreme rainfall intensities and atmospheric temperature (and, to some extent, moisture) and described the contribution of observational and climate modeling studies to our understanding of how subdaily rainfall extremes has responded—and might continue to respond—to anthropogenic climate change. However, there are many limitations to our present understanding. Observations of subdaily rainfall are typically short, have been subject to changes in instrumentation technology over time, and are only available at a small number of locations worldwide.

Climate modeling studies also have difficulty in resolving the processes that cause short-duration rainfall extremes, while simultaneously modeling the large-scale conditions in which the local extreme rainfall events are embedded. Finally, engineering design of flood infrastructure is often based on events that are much more extreme than commonly considered in climate studies, and it is not known whether the conclusions from climate studies that focus on “moderate” extreme events are also valid for the extremes used for urban planning and the design of hydraulic structures.

A concerted research effort is required if we are to provide a coherent global picture of potential future change. This section outlines research areas that we hope will lead to a better understanding of future changes in extreme subdaily rainfall.

6.1. Improving Monitoring and International Coordination of Subdaily Rainfall Measurements

As discussed in section 3, there is a need to create a global subdaily data product that can be used to evaluate systematic changes in subdaily extreme rainfall intensity. This will require negotiations most likely at the individual country level. In many countries there are more subdaily rainfall measurements available than are included in global databases such as HadISD. Timelines for providing data, and mechanisms for ongoing updates, would be required, potentially drawing on existing frameworks for data provision such as the World Meteorological Organization Global Framework for Climate Services and international coordination projects such as World Climate Research Program’s Grand Challenges on Extremes.

Ideally, data would be provided as quality-controlled 1 min continuous time series, although it seems unlikely that quality control procedures could be standardized worldwide. Accompanying metadata on instrument type, location, and typical maintenance schedule would ensure that inhomogeneities in the records could be adjusted as required for studies with different purposes.

A central database to store these data would require significant information technology support as data are most likely to be in a variety of formats. Alternatively, a common format for data transfers could be mandated but is still likely to require significant investment in processing data. A database with the capability to aggregate data to a range of event durations would be useful for distributing data to users.

6.2. Developing Blended Subdaily Rainfall Products

With long time series of radar data now available in a number of locations, there are good opportunities for combining understanding of spatial patterns with temporal trends in extreme rainfall. However, given the difficulties in converting the radar reflectivity measurements to rainfall rates, blended products of combining gauge and radar measurements hold the most promise. Work on blended products has been investigated for some time [*Krajewski*, 1987; *Sinclair and Pegram*, 2005; *Berndt et al.*, 2014]; however, work in the context of verifying RCM rainfall projections has recently led to more interest in this research area [*Kendon et al.*, 2014]. Further investigations are required to understand how well such methods perform for the most intense rainfall rates, as well as the optimum way of combining the two-radar and gauge-based products.

6.3. Improving Techniques for Detecting Change

The limited availability of rainfall gauging stations with long high-quality records has meant that studies increasingly use advanced statistical techniques to evaluate changes in spatial rainfall patterns [*Davison et al.*, 2012]. Spatial extreme value techniques such as regional frequency analysis [e.g., *Fowler and Kilsby*, 2003], Bayesian hierarchical models [*Cooley et al.*, 2007; *Cooley and Sain*, 2010], extremal copulas [*Demarta and McNeil*, 2005], and max-stable approaches [*Schlather*, 2002; *Padoan et al.*, 2010; *Davison et al.*, 2013; *Huser and Davison*, 2013; T. F. Smith, Max-stable processes and spatial extremes, unpublished manuscipt, 1990], allow space-for-time substitution and thus enable inference of change over shorter periods of record. Without using spatial techniques, it is likely that studies investigating trends will remain inconclusive for many decades to come [*Frei and Schar*, 2001; *Zhang et al.*, 2004; *Westra and Sisson*, 2011]. However, practical applications of spatial extreme techniques to detect trends in extreme rainfall are still limited [e.g., *Westra and Sisson*, 2011].

A number of recent contributions have also been made on threshold-excess approaches [*Northrop and Jonathan*, 2011; *Thibaud et al.*, 2013], which permit several extreme events to be analyzed in a typical year. The r-largest approach [*Coles*, 2001] is an alternative method for simulating more than one event per year. However, a detailed comparison of the advantages and disadvantages of different representations of extremes is also still lacking.

Most studies of spatial rainfall assume concurrent records at each point location [*Padoan et al.*, 2010]. In most cases, however, the record lengths at each gauge will be different, and many gauges may have values missing from some portion of their record. Furthermore, the technology used to measure subdaily rainfall has changed over time, so that it may also be necessary to separately test for step changes before and after the change in gauging technology and gradual changes due to long-term trends [*Westra and Sisson*, 2011]. More work is therefore needed to develop a consistent approach to account for the specific challenges of using the subdaily rainfall observing network to test for changes to subdaily extreme rainfall intensity.

Finally, based on the empirical results described in section 2, it is likely that the scaling relationship of rainfall extremes between longer (e.g., daily) and shorter time scales (e.g., subhourly) is likely to change. There has been significant research on the temporal scaling relationships for historical climate rainfall [*Mandelbrot*, 1982; *Lovejoy and Schertzer*, 1985], and these relationships are being used increasingly to estimate the statistics of extreme rainfall jointly at multiple time scales [*Burlando and Rosso*, 1996; *Koutsoyiannis et al.*, 1998; *Menabde et al.*, 1999]. Evaluating trends in the scaling parameter over time is therefore likely to be of significant importance in better understanding how IDF curves will change in a future climate.

6.4. Improving the Capacity of Climate Models to Simulate Subdaily Rainfall Extremes

Although both GCMs and low-resolution RCMs are relatively poor at simulating subdaily precipitation—and particularly the extremes—some improvements have occurred over recent years. These have been related largely to improvements in model resolution and modifications to (or reduced reliance on) convective parameterizations. For GCMs, improvements in convective parameterization schemes are vital, although the inherent limitations of the convection parameterization approach may mean that it will not be possible to investigate subdaily rainfall adequately on a global scale in the near future. One avenue to improve GCMs may be to introduce cloud resolving models as superparameterizations. In contrast, to improve RCMs it will be possible to reduce model resolutions to convection-permitting scales, and thus remove the convection parameterization.

With more powerful computers (e.g., more processors), it will likely become commonplace to run regional kilometer-scale RCMs on increasingly large domains over different parts of the world. This may not only provide insight into changes to subhourly rainfall but also the potential impacts on larger scales. Work in this area should keep up to date with NWP forecast model developments at these resolutions, which are still being improved to better represent convective cores, microphysical processes, and subgrid turbulence. It is also hoped that improvements in the quality and availability of subdaily rainfall observations will continue and facilitate future climate model developments.

6.5. Developing a Framework for Understanding the Capacity of Climate Models to Simulate Rainfall Extremes

Given the challenges associated with observing subdaily rainfall, climate models such as RCMs are likely to remain the dominant source of information for predicting future changes. How can we evaluate whether climate models simulate the physical processes needed to simulate short-duration rainfall extremes?

We argue that there are some necessary features of rainfall that should be correctly simulated, and this lends itself to a set of diagnostic measures for assessing climate model capability. In addition to standard metrics to evaluate whether the model captures the correct statistics of subdaily extremes (e.g., whether the 99 percentile rainfall is consistent between the model and the observations for different rainfall durations), physically based metrics which might shed light on whether the model is simulating the correct physical processes might include the following:

1. *Seasonality*: Does the model simulate rainfall extremes at the correct time of year?
2. *The diurnal cycle*: Does the model simulate rainfall at the correct time of day?
3. *Temperature and humidity dependency:* Does the model simulate the observed association with atmospheric temperature and humidity, including possible super-CC scaling and/or a decline at high temperatures?
4. *Temporal scaling*: Does the model simulate the correct scaling relationships between different levels of aggregation (e.g., subhourly versus multiday events)?

5. *Synoptic maps*: Are the composite maps of pressure and wind fields and associated attributes (e.g., position of the jet stream, troughs, and cyclonic systems) similar for the most extreme observed and modeled events similar?
6. *Spatial structure and temporal evolution of rainfall events*: Are the model-simulated rainfall fields and their evolution realistic?

Given the role of antecedent catchment moisture prior to flood-producing rainfall events, it is also necessary to evaluate whether the timing and intermittency of rainfall events are correctly captured, as well as the interaction between subdaily extreme rainfall and large-scale modes of climate variability, such as the El Niño-Southern Oscillation (ENSO) phenomenon.

6.6. Bridging the Gap Between Atmospheric Science and Flood Hydrology

To estimate flood risk, flood hydrologists often require information on extreme rainfall in specific forms, which enable calculation of flood magnitudes at specified probabilities of being exceeded. Examples of information requirements include the following:

1. *Intensity-duration-frequency (IDF) relationships*: These relationships describe the intensity of rainfall as a function of the storm burst duration and the exceedance probability of that event and are required for most event-based flood estimation techniques;
2. *Depth-area curves*: These curves describe the relationship between the intensity of rainfall occurring at a point, and the average intensity of rainfall over some geographic area, and are required to convert IDF information (which applies to a point) to catchment-average rainfall intensity.
3. *Joint probability between extreme rainfall and antecedent conditions*: The antecedent precipitation index [*Cordery*, 1970] is sometimes used to provide a measure of how wet the catchment is likely to be prior to the flood-producing rainfall event. A drier (wetter) catchment prior to flood-producing rainfall events in a future climate may lessen (worsen) the impact of a possible intensification of extreme rainfall, and therefore needs to be taken into account when estimating flood risk.
4. *Joint probability between extreme rainfall and other meteorological variables*: Often, hazards can be caused by a combination of multiple variables being in an extreme state. For example, extreme rainfall combined with elevated storm surge can lead to more severe impacts than when either variable is extreme in isolation, and therefore, research is needed on how the joint probability of these variables will change in a future climate.
5. *Probable maximum precipitation* (*PMP*): In many cases, flood risk is determined based on very rare events that potentially have extremely significant consequences. Information on whether extremes commonly analyzed in climate science are controlled by the same factors (and thus can be expected to change in the same way) as very rare extremes is therefore needed for the design of critical flood-protection infrastructure.

To estimate the likely risk of flooding in a catchment under a warmer climate, it is important that researchers consider not only the potential for changes in the intensity and/or frequency of extreme flood-producing rainfall events but also the spatial extent of the extreme rainfall events, the antecedent moisture, and the interaction with other flood-producing variables. These features vary with the “type” of rainfall (e.g., local convective versus large-scale) [*Svensson and Berndtsson*, 1996], suggesting that even geographically nearby catchments with different physiographic features (e.g., size and moisture storage capacity) [see *Merz and Bloschl*, 2003] may exhibit very different responses if the prevalence of different types of rainfall changes in the future.

Our review of the literature on future changes to extreme subdaily rainfall found very limited information on any of these topics. A significant research effort is therefore required to provide the information needed to estimate flood risk in a future climate.

7. Conclusion

This review has examined evidence for the intensification of subdaily extreme rainfall due to anthropogenic climate change and has described the main physical arguments for the association between subdaily extreme rainfall intensities and atmospheric temperature. We also examined the nature, quality, and quantity of information needed to allow society to adapt successfully to predict future changes and discussed the roles of observational and modeling studies to help us better understand future change.

The main conclusions from this review are that

1. A clear relationship between extreme rainfall intensity and atmospheric temperature has been identified in a number of studies, and the relationship is much more complex than would be suggested by the hypothesis that extreme rainfall will scale with the water-holding capacity of the atmosphere (as described by the Clausius-Clapeyron relationship). Rates of increase of up to double the CC rate have been observed in multiple observational and modeling studies for subdaily extremes for temperature ranges between approximately 12°C and 22°C and decreases in rainfall intensities with temperature have also been found above ~24°C. Further research is needed on the extent to which these observed scaling relationships can be applied to climate change predictions.
2. Evidence indicates that the intensity of subdaily (and particularly, hourly or subhourly) extreme rainfall is more sensitive to changes in local atmospheric temperature compared to the intensity of daily-scale rainfall. The results from daily-scale observational or modeling studies therefore are unlikely to be directly transferrable to subdaily time scales.
3. Based on studies examining rates of change in daily extreme rainfall, it is likely that there will be substantial differences depending on the geographic location. However, the relative scarcity of observational and modeling studies focusing on subdaily time scales mean that it is not possible to make direct conclusions on regional patterns of trends at the subdaily time scale.
4. Present-day global climate models have limited ability to simulate subdaily precipitation extremes correctly as they do not explicitly resolve convective processes. This casts strong doubts on future projections of changes in subdaily precipitation extremes derived from these models. Increasingly, however, regional climate models are being run at convection-permitting resolutions, with early studies showing promising improvements to key attributes of subdaily rainfall.
5. Changes to subdaily rainfall will significantly affect the magnitude and frequency of urban and rural flash floods. A better understanding of future changes in extreme subdaily rainfall intensities is therefore needed to help society adapt to these potential changes.

This review argues that a focused international research effort is needed to better understand future changes to subdaily extreme rainfall. Research areas were identified to help produce a more thorough understanding of the relationship between large-scale warming and subdaily extreme rainfall intensity. These research areas cover a range of fields of specialization and should focus on (1) improving both gauge-based and remotely sensed observing networks; (2) developing and applying extreme value techniques that can handle a diversity of artifacts associated with the subdaily observing network; (3) applying convection-permitting kilometer-scale models to climate change studies and using a diagnostic approach to assess the performance of these models in simulating short time-scale rainfall; (4) understanding the relationship between subdaily extreme rainfall and large-scale drivers for extreme rainfall, including an understanding of how those drivers might change in the future; (5) understanding the apparent decline of extreme rainfall intensity for temperatures above ~24°C, including whether this decline can be expected to continue in a warmer climate; and (6) strengthening the link between climate science and impact science, focusing on understanding how extreme rainfall leads to flood risk. Only through a concerted research effort will we be able to better understand each of these facets of subdaily rainfall, and thereby develop a more complete understanding of the likely future intensity and frequency of short-duration rainfall extremes that can be expected in a warmer future climate.

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